CAREER AND TECHNICAL EDUCATION AND CURRICULAR INTENSITY: OUTCOMES OF TRACKING, DROPOUT, AND COLLEGE

by

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Abstract

In recent years, career and technical education (CTE), formerly labeled vocational education, increasingly has enrolled the full range of academic achievers. CTE research needs to take account of the quality and quantity of academic courses (*curricular intensity*) of students' experiences. I present three papers to address important aspects of the new directions in CTE. They leverage survey responses and transcripts from 9,400 students in the *High School Longitudinal Study* of 2009 to report nationally representative estimates. In the first paper, I compare curricular intensity levels of CTE and non-CTE students and then compare curricular intensity within CTE by career cluster using ordinary least squares regression analyses. In the second and third papers, I add curricular intensity to analyses of two common CTE research topics: high school dropout rate, college enrollment. I use discrete time hazards models and logistic regression analyses, respectively, to estimate the benefit of students' progress in a CTE program. I find that levels of curricular intensity do not differ between CTE and non-CTE students, but levels of curricular intensity do differ within CTE, by career cluster. These findings suggest that CTE is still mildly sorted—a possible sign of structural inequality. I also find that students with low curricular intensity have the greatest odds of dropping out of high school and that participation in CTE reduces dropout probability. Finally, I find that participation in secondary CTE is not significantly associated with post-secondary enrollment, nor the decision to attend a two- or four-year degree among college enrollees. These findings collectively emphasize the importance of curricular intensity as a critical variable in future research on CTE.

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Dedication

There can only be one person to whom this dissertation—all my educational success—can truly be dedicated. To the person who helped me rediscover joy in school when I had lost it before finishing my undergraduate degree. To the person who stuck by my side through that degree and two more. To the mother of my children. To Lauren, my wife.

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Chapter I

Introduction

Career and technical education (CTE) came under heavy criticism several decades ago when it was known as vocational education for its role in tracking students (Lucas, 1999; Oakes, 1985; 1994; Rosenbaum, 1976). Tracking occurred when a student's academic course schedule determined whether he would enroll in vocational education courses. Often, the tracks were rigid, not allowing students to move between tracks (Rosenbaum, 1976). Students enrolled in a vocational track were less likely to continue to post-secondary education after high school graduation (Arum & Shavit, 1995; DeLuca, Plank, & Estacion, 2006). This was commonly seen as a negative outcome because those in vocational education were disproportionately from low-income families, with parents who had less formal education. Tracking was seen as a method of maintaining intergenerational inequality (Lucas, 1999).

Today, schools do not formally engage in tracking practices and enrollment in CTE is open to all students regardless of the rigor of their academic courses (Giani, 2017). The contrast in enrollment patterns between CTE today and vocational education of prior years may be found in students' academic profiles. Once a similar, homogenous academic group, current-day CTE may be filled with students of widely varying academic backgrounds—a heterogenous group (Dalton, Lauff, Henke, Alt, & Li, 2013). By removing formal curricular tracks and allowing all students to enroll in CTE, educators posed an unstated hypothesis: CTE is no longer connected to tracking.

This hypothesis would be empirically supported if the rigor of a student's academic course schedule was unrelated to their participation in CTE in any way. An evaluation of the relevancy of one's academic rigor to CTE participation must be conducted in two parts. The first part needed to determine whether academic rigor is connected to CTE participation is likely self-evident: differences in the academic background between CTE participants and non-CTE participants must be evaluated.

This was regularly evaluated in tracking research near the end of the 20th century (Oakes, 1985; Gamoran & Mare, 1989; Lucas, 1999; Sørenson & Hallinan, 1977). Its regular evaluation was important because it showed that students were segregated into or out of then-vocational education by academic background. The change to this policy now allows for students of all academic backgrounds to participate in CTE, which increased the likelihood that no difference between CTE and non-CTE students exists.

The second part of the evaluation into the relevancy of academic rigor to CTE may not be as readily obvious because of the colloquial tendency to refer to CTE as a group of similar courses, in the same way that mathematics or English courses are similar courses. However, unlike those subjects where all students are placed on a single path forward (e.g., algebra I to algebra II; English 9 to English 10), CTE offers multiple paths from which students choose (Advance CTE, n.d.). Therefore, in evaluating the relevancy of academic rigor to CTE participation, the second part of the evaluation is conducted by comparing the academic background of CTE participants across each of the CTE career fields, known as career clusters.

This comparison within CTE has seldom been evaluated (Oakes, 1983), and not at all in recent decades. This gap in the literature is important because the change to allow students of all academic backgrounds to participate in CTE increased the likelihood that differences between career clusters exists. The potential for unequal sorting by career cluster may be made clearer by restating with an example: manufacturing must enroll students of the same academic caliber as computer science in order for academic rigor not to be relevant in CTE participation.

So far, no research has been conducted that analyzes the academic course schedule of CTE students to understand whether CTE is still related to academic schedules. The lack of research on this topic mirrors the lack of discussion in the public or among policymakers about the relationship between CTE and tracking. This is not to suggest a lack of discussion generally. Press mentions (Jacob, 2017) and state legislation (Advance CTE & ACTE, 2018) on CTE has increased year after year in the last decade, with nearly all of the attention encouraging increased participation. Before encouraging wholesale participation in CTE, it is incumbent on researchers to determine whether tracking does exist between career clusters. If so, we need to ask: What are the commonly observed outcomes for participants after adjusting for their academic schedules?

If CTE participation is not yet fully divorced from considerations of academic rigor, then the same questions of past tracking literature are still relevant and important today: Does CTE or any of its career clusters predominately attract struggling students from low socioeconomic backgrounds (Gamoran & Mare, 1989)? Does participation in CTE harm a student's chances of continuing to college after high school (Arum & Shavit, 1995)? Does CTE serve all students equally (Oakes, 1983; Royster, 2003)?

The stakes for answering these questions about CTE are high because CTE is entrenched in high schools across the United States, in virtually every city and school district. A full 85% of public high school graduates earn CTE credits within a career cluster (National Center for Education Statistics, 2009) and the average high school student graduates with approximately as many CTE credits as math or science credits (Hudson, 2013). Where vocational education was once reserved for a specific segment of students in prior decades, CTE is now a common experience for high school students in the United States.

Answering the above questions requires researchers to quantify the rigor of a student's academic schedule. An early method of portraying a student's level of academic coursework relied on observing a student's enrollment in a single, telling academic course, due to the rigid separation of course tracks (Rosenbaum, 1976). Subsequent efforts included asking schools (Oakes, 1985) or students themselves (Gamoran & Mare, 1989) about the students' track placement. Later efforts were made to develop more comprehensive, subjective (Lucas, 1999), and objective (Adelman, 1999; 2006) algorithms to summarize student involvement and place in academic coursework.

A recent refinement on Adelman's (1999; 2006) curricular intensity measure now allows for the facile measurement of academic coursework in multiple datasets, including those that reflect the current state of CTE. Additionally, the new refinement performs slightly better than Adelman's original and is easier to interpret. It measures the intensity of a student's academic experience by combining the quantity of academic courses with their quality (Austin, 2020). Curricular intensity is, currently, the best measure of the rigor of a student's academic coursework.

This dissertation uses curricular intensity to re-examine questions from past tracking research that remain relevant today. In the paragraphs below I provide a brief introduction to the three papers that constitute this dissertation, each addressing a different question. I also describe how I measure CTE participation in a new way that better represents CTE participation than previously constructed measures.

The first paper (Chapter II) investigates the fundamental and primary question: Is CTE participation connected to academic rigor? As discussed above, this question must be addressed with two comparisons. The first is between CTE and non-CTE students; the second is within

CTE, between career clusters. I compare each of these groups on their levels of curricular intensity, which represents each group's academic rigor. This is important because if academic rigor is still associated with CTE, then many hard questions that were asked of vocational education should be asked of CTE. Additionally, if CTE remains connected to academic rigor, research into CTE will be improved by including curricular intensity in analyses.

The second paper (Chapter III) moves in this direction by introducing curricular intensity into analyses of the long-noted association between CTE and decreased rates of high school dropout. The introduction of curricular intensity into this topic explores new insights into the question: Who benefits most from CTE—low-income or low-engagement students (Dougherty, 2018; Kemple & Willner, 2008; Plank, 2001; Plank, DeLuca, & Estacion, 2008; Schargel & Smink, 2014; Stone & Alfeld, 2004). This paper uses discrete time hazards models to allow for changing levels of engagement throughout high school. This method also allows me to account for the relationship of CTE on dropout rates as it may vary by a student's year in school (Gottfried & Plasman, 2018). The analyses will contribute to the ongoing discussion about who CTE will help the most.

Given that students are supposed to be prepared for both college and career by participating in CTE (Brand, Valent, & Browning, 2013), the third paper (Chapter IV) examines post-secondary destinations of CTE participants. This is done with adjustments for students' curricular intensity to account for the increased societal emphasis on academics and college-going, compared to prior decades. This is important because of CTE's growing popularity as a resource to support both college and career readiness.

Across all studies I use a measure of CTE participation that is consistent with the current design of CTE, which was updated in 2006 and differs from prior CTE participation design models (Gordon, 2014; Threeton, 2007). The new design introduced and emphasized programs of study, which refers to cohesive and targeted course offerings. Accordingly, my measurement of CTE participation requires student course taking to be within a program of studies. The three papers in this dissertation are the first to use nationally representative data to measure CTE participation in programs of study.

Throughout the dissertation, I use curricular intensity to represent the quality and quantity of a student's academic course schedule. However, this straightforward interpretation becomes more nuanced after I adjust for other important covariates such as background and prior achievement, which explain some of the reasons for student's curricular enrollment choices. After statistically adjusting for these variables that explain reasons for curricular intensity, the remaining reasons for observed curricular intensity are likely latent, such as engagement and ambition, or differences in structural opportunity. An extended discussion on interpreting curricular intensity after including adjustment variables in analyses can be found in Chapter II.

This dissertation is a valuable addition to the literature by extending knowledge in several ways. It demonstrates how CTE, under its current design, can be observed appropriately (i.e., in programs of study) in a national dataset. It provides the first descriptive outlook on how the academic coursework of CTE students compares to non-CTE students. It provides the first descriptive outlook on how academic coursework of CTE students varies within CTE, by career cluster. It revisits important questions of CTE's relationship with high school dropout and college enrollment rates after adjusting for academic coursework.

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Chapter II

Beyond the Treatment of CTE as a Monolith:

Differences in Academic Curricular Intensity Between CTE Career Clusters

Introduction

For most of the 20th century, the high school experience of American public education students was defined by the quantity and quality of their academic courses, which in turn determined whether they participated in vocational education (Oakes, 1985). Students who participated in rigorous academic courses were not enrolled by their school counselors into vocational coursework (Rosenbaum, 1976). The ubiquitous curricular divisions into or out of vocational education by academic credentials were commonly called tracks: the college track and the vocational track. As with train tracks, each track led to a different post-high school outcome and switching tracks was difficult (Rosenbaum, 1976). Although track placement was based on academic performance and rigor—which may appear fair and impartial, students' academic performance and rigor was associated with their socioeconomic status (Coleman et al., 1966). As such, low socioeconomic status students tended to be tracked to vocational education, and high socioeconomic status students tended to be registered for the college track (Gamoran & Mare, 1989).

Critics suggested that tracking served as a machine for reproducing societal inequalities, and, as the 20th century ended, schools largely dismantled their formal tracks. The new curricular model allowed all students access to rigorous academic courses (Oakes & Lipton, 1992). By increasing students' access to rigorous academic courses, schools intended to foster increased academic preparation for all students. The removal of formal tracking also allowed students in rigorous academic courses to enroll in vocational courses. To best serve students of all academic levels and to avoid tracking participants away from college, vocational education was redesigned to more explicitly support academic development and to include offerings that appealed to all students (Threeton, 2007). During the redesign, vocational education was renamed career and technical education (CTE) to rebrand it and distance it from its prior connection to tracking (Association for Career & Technical Education [ACTE], n.d.). The changes to support all students with rigorous academics and relevant CTE courses resulted in the creation of a single track in school instead of multiple tracks.

As tracks were removed, the average number of academic credits earned by high school students increased (Hudson, 2013). Another trend that has been observed after removing tracks is that CTE now enrolls more high-SES and high-math students than previously (Dalton, Lauff, Henke, Alt, & Li, 2013). These trends suggest that students are not sorting, or being sorted, into or out of CTE as much as in prior years.

The change in school programs to remove tracks did not address potential sorting occurring within CTE, between career preparation areas—known as career clusters. As curricular domains speak to students' personal interests, students select the career cluster in which they want to participate. The career options supported by CTE span broad segments of the labor market, from food preparation to engineering (Advance CTE, n.d.). As students select an area of CTE to participate in, their options are limited to the CTE areas that their school has chosen to offer. As schools determine available course offerings, and students select into a CTE field, they are making choices about career fields that inherently differ in level of societal prestige, income, and educational requirements.

In addition to these conditions which may foster sorting within CTE, human nature suggests that sorting is a natural tendency (Ames, Jenkins, Banaji, & Mitchell, 2008; Bahns, 2017). It is observed among children in the same classroom, as they gravitate to become friends or work with other students whom they perceive to be similar to themselves (Lareau, 1987). In light of this tendency, the demonstrated history of curricular sorting by track (Lucas, 1999), and differences in CTE fields themselves, I ask the question whether sorting akin to tracking is happening within CTE, between the career clusters?

A new refinement (Austin, 2020) on an established instrument (Adelman, 1999; 2006) that measures curricular intensity enables me to investigate my research question by providing a way to determine who is participating in different CTE career clusters. By measuring a student's quantity and quality of academic coursework as curricular intensity, I can measure the strength of a student's academic background. This allows me to create an academic profile of students in each career cluster (Advance CTE, n.d.). This new refinement on the measurement of curricular intensity performs better than prior versions of the instrument which would not be useful in this investigation because they were burdensome to set up and only available in datasets collected during the vocational education era (Austin, 2020).

In this chapter, I will review relevant research literature and summarize what is known about sorting in vocational education and sorting in CTE to address my research question. I will then present the methods I selected for the investigation of my question, including how I measure CTE participation in a national data set, the construction of my measure of curricular intensity, and how I look for evidence of sorting within CTE career clusters. After presenting my results I proceed to discuss their implications for policy and future CTE research. I conclude an outline of research questions that arise from my findings.

Literature Review

The rigid grouping of students into curricular groups called tracks was a normative feature of American public education throughout the 20th century (Lucas, 1999; Oakes, 1985). Students were either placed in the college track or the vocational track (sometimes schools offered a third track commonly referred to as the general track). The determination of which track a student would participate in was frequently made by a school counselor who placed a heavy emphasis on the student's prior academic performance (Rosenbaum, 1976). Prior performance is a strong predictor of future academic performance, but is also a strong correlate of socioeconomic status (Coleman et al., 1966; White, 1982). The result of track placement determined which academic courses the student participated in and the extent to which the student would participate in vocational courses. Often, track placement was rigid, not allowing movement between tracks and not permitting access to their respective courses (Oakes, 1985; Rosenbaum, 1976).

This rigid form of tracking was justified within American public schools because some educators reasoned that by grouping students into classes of similar ability levels and interests, the students would be able to make faster learning gains (Hallinan, 1994). However, although this grouping structure benefitted advanced students, those in the vocational track saw little benefit and potential harm through lowered probability of enrolling in college after graduating from high school (Ainsworth & Roscigno, 2005; Arum & Shavit, 1995; DeLuca, Plank, & Estacion, 2006). The students most often enrolled in vocational education were those from homes with parents who had less formal educated and lower incomes—background characteristics that consistently correlate with academic performance (Coleman et al., 1966; Oakes, 1985; White, 1982). In essence, school tracks were an efficient sorting mechanism that appeared objective but disproportionately routed students from advantaged families towards college and higher lifetime wages (i.e., social class perpetuation; Gamoran & Mare, 1989; Hollingshead, 1949; Lucas, 1999; Oakes, 1985; Rosenbaum, 1976).

Formal tracking practices largely disappeared toward the close of the 20th century as the landmark report on American public education, *A Nation at Risk*, spurred increased academic rigor for all students (Guthrie & Springer, 2004). Schools also endured criticism for tracking practices (Oakes, 1985), and many industries served by the vocational track began changing required skills because of the introduction of the personal computer (Ames, 1988; Baten, 2016).

As the vocational track disappeared, the overall number of average credits earned by students in core academic subjects rose and the average number of vocational credits earned by students declined (Hudson, 2013). At the start of the 21st century, vocational education began to change its offerings to better align with technological advancements in industry and to better serve the full range of students at all achievement levels. These changes were formalized in a federal funding bill in 2006, known commonly as Perkins IV, and vocational education was renamed to career and technical education (CTE) to punctuate the change and effect a rebrand (ACTE, n.d.).

From the end of tracking to the present day, the average reading and math test scores of CTE students have been rising (Silverberg, Warner, Fong, & Goodwin, 2004), indicating that CTE is enrolling students with higher academic ability than was observed in previous years (Dougherty & Lombardi, 2016). One could plausibly argue that the scores rose because of the increased academic course loads that occurred for all students since schools were de-tracked (Hudson, 2013). This argument is weakened by the increased participation in CTE among the highest quartile of high-achieving students and high-SES students (Dalton et al., 2013; Levesque, Laird, Hensley, Choy, Cataldi, & Hudson, 2008). The most plausible explanation of this change in CTE students' academic profiles is that CTE is attracting a more heterogenous group of students than in previous decades.

As students participate in CTE, they select their courses within CTE, rather than following a nationally uniform and prescribed path for all students as occurs in many core subjects (e.g., English 9 to English 10, etc.). CTE's framework encompasses a wide diversity of career options. A national organization comprised of state CTE leaders from all 50 states, known as Advance CTE, recognizes 16 different career clusters for CTE offerings such as manufacturing, agriculture, or finance (Advance CTE, n.d.). Within each of the 16 career clusters there may be a potentially unlimited number of career pathways (as determined by schools based on local needs), although Advance CTE names 79 plausible pathways. For example, within the agriculture career cluster, there may be pathways that support preparation for a career in agribusiness, food production and processing, or environmental systems. Different schools may advertise the same pathway but offer different courses to support the students' preparation for that career path. These course combinations, set by schools and approved by the district and state, are called programs of study (Advance CTE, n.d.).

Each CTE pathway prepares students for careers which inherently differ in level of required post-secondary education (Carnevale, Smith, & Strohl, 2010), prestige (Stevens & Featherman, 1981), and income (Carnevale, Strohl, Cheah, & Ridley, 2017). These features of the labor market have the potential to create a tracking structure within schools if CTE career cluster selection is based on academic achievement. The defining difference between former tracking practices and possible new tracking practices is that, previously, students were tracked into or out of CTE, whereas today they may be tracked within CTE, sorted between career clusters (Giani, 2019). For example, high-achieving students may sort into STEM careers and related courses instead of agriculture. Vice versa, low-achieving students may select careers and training in agriculture instead of STEM.

A new refinement on an established instrument for measuring a student's level of academic rigor would allow for detection of sorting patterns occurring in the most current iteration of CTE. The instrument, known as curricular intensity, is a transcript-based measure of the quantity and quality of a student's academic course taking. The original form of measuring curricular intensity used an algorithm that combined 13 curricular summary statistics to produce a single value that represented the student's overall level of curricular intensity (Adelman,1999; 2006). This measure comprehensively and objectively captured each student's full academic experience, balancing quality and quantity of coursework.

One of the strengths of Adelman's curricular intensity measure is that it removed the subjectivity inherent in prior curricular summary measures such as course-based indicators (Lucas, 1990, 1999) or self-reported track membership (Gamoran & Mare, 1989). However, a weakness of Adelman's measure is that it is difficult to replicate into other datasets because of its complex, and non-systematic construction (Austin, 2020).

Recently, Austin (2020), showed that a student's curricular intensity could be calculated with only four of Adelman's 13 curricular summary statistics. This reduced-form algorithm closely approximates Adelman's full version while simultaneously being more clearly defined and imposing a lighter burden of data collection and analysis for researchers (Austin, 2020). This refined version of curricular intensity performs well in measuring the quantity and quality of a student's academic experience and is more predictive of future academic outcomes such as college enrollment and college graduation than SES (Austin, 2020). Therefore, in the present study, I use it to measure potential tracking within CTE. The improved instrument measures two elements that are at the core of tracking: routine differences in academic course taking while in high school and college entry after high school.

Method

Data and Sample

Tracking involves patterns in academic course taking that correlate with patterns in CTE course taking, making it imperative to select a dataset that had transcript data about all courses students enrolled in. Additionally, due to the changing nature of vocational education to CTE, it was important to use data from students who entered high school after Perkins IV was passed in 2006. Lastly, because of the large number of categories within CTE—16 career clusters at the most aggregated level—it was important to use a dataset large enough that it would yield usable sample sizes for each grouping, even for the less common career clusters.

The *High School Longitudinal Study* of 2009 (HSLS:09) meets these requirements. It includes data on a nationally representative sample of 25,206 students who were enrolled in ninth grade during the 2009-2010 school year. Students participated in HSLS:09 through a two-stage sampling process in which schools were sampled, followed by sampling students. Baseline information about school programs and offerings were collected via surveys from school counselors in the fall of 2009. Transcripts were collected from schools in the fall of 2013, which was immediately after the completion of high school for students who graduated on-time.

I restrict my sample to those students from public high schools to reflect the most typical American high school experience. I exclude students from public schools in which the school counselor indicated CTE programs were not offered. Students were included in the sample if they began ninth grade in the 2009-2010 school year and if they graduated four years later at the conclusion of the 2012-2013 school year. This restriction ensures that all students had the same length of time to complete all courses and accrue academic credits—the components that are needed to calculate curricular intensity. Students were also excluded if they transferred high schools because of the inability to verify whether a student's second school offered courses within the same CTE career clusters as the student's first school, which, potentially interrupted mobile students' CTE experiences. Students were not included in my sample if a transcript was not on file. This sample for this study includes 9,460 students. I further restrict my sample to those without missing values for the covariates described below, which reduces the sample by 8% to a final analytic sample of 8,680 students.

I do not judge this reduction in sample size to be problematic because it is near 5%, which is the recommended threshold of missingness for which listwise deletion outperforms other missing data techniques such as multiple imputation (Allison, 2002). Additionally, I find no differences descriptively between the two samples. Appropriate sampling weights are used throughout to create nationally representative estimates.

Measures

Curricular intensity. Curricular intensity refers to the quantity of academic courses taken, as well as the rigor, or quality of the courses taken (Adelman, 1999; Austin, 2020). It is comprised of four contributing values: the highest math course a student took in high school, the number of laboratory science credits the student earned, the number of English credits the student earned, and whether the student ever completed an advanced placement (AP) course. Values for the highest level of math a student completed were coded zero for no math or math below algebra 1, coded one for algebra 1, coded two for geometry, coded three for algebra 2, coded four for trigonometry or other advanced math topics, coded five for pre-calculus, and coded six for calculus.

To combine the four curricular indicator values into a meaningful single value of curricular intensity, Austin recommends conducting a confirmatory factor analysis (CFA). As its name infers, CFA is used to confirm the relationship between the observed variables and an unobserved, latent factor (Thompson, 2004)—in this case, curricular intensity. The CFA analysis produces factor loadings that represent how much or how little each of the four factors contributes to the latent construct of curricular intensity for the given sample. Values for the factor loadings range from 0 to 1, where higher values indicate greater representation of the latent construct.

The factor loadings are then used as a scalar, multiplied by the raw values of all members of the sample. The process is represented mathematically as follows:

$$currint = \lambda_1(highmath) + \lambda_2(english) + \lambda_3(coresci) + \lambda_4(AP)$$

where λ is the standardized factor loading of each variable on the latent curricular intensity indicator from the CFA results. As an example, consider a student who took algebra 2, three English credits, two science credits, and never took an AP course, and is in a sample in which the highest math factor loading is 0.8, the English factor loading is 0.5, the science factor loading is 0.6, and the AP factor loading is 0.3. The curricular intensity value for the student would be 5.1 (result from 0.8 * 3 + 0.5 * 3 + 0.6 * 2 + 0.3 * 0 = 5.1). This process is conducted for each dataset and the standardized factor loadings for HSLS:09 are provided by Austin (2020).

Adjustment variables. I use adjustment variables that represent background and prior achievement, given the historical relationship of these constructs with tracking. I include measures of SES, race, unweighted high school grade point average (GPA), and math test scores from the beginning of 9^{th} grade that are all available in HSLS:09. The math test focused on algebraic reasoning and was administered in a computer adaptive format.

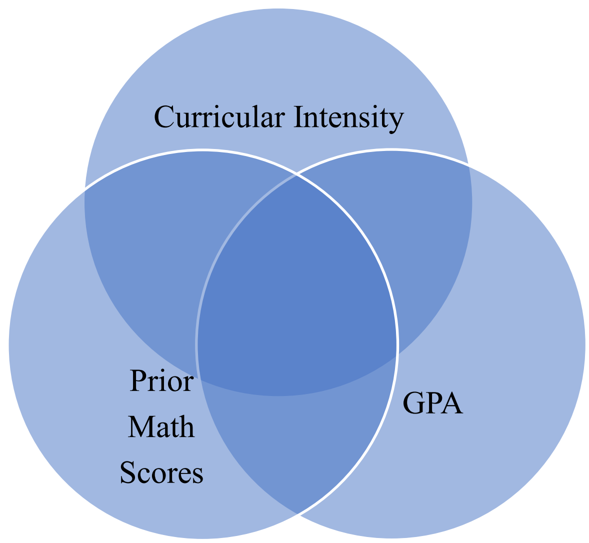
These variables are included because they represent important constructs known to correlate with and explain tracking practices. By including them, the interpretation of curricular intensity changes to represent the quantity and quality of academic courses after adjusting for background characteristics and prior achievement. This section will explore what curricular intensity represents in statistical models when included alongside variables for background characteristics and prior achievement.

Curricular intensity represents a phenomenon—something that happened. The background and prior achievement variables that are included represent explanations of why that phenomenon occurred. If the adjustment variables explain all of the phenomenon then the phenomenon itself does not need to be observed or explained in subsequent statistical models; it is perfectly understood. If the adjustment variables do not explain all of the occurrences in the phenomenon, then something else is occurring to influence the phenomenon that is left unexplained by the adjustment variables.

This idea can be thought of in simple terms as a Venn diagram. One circle represents the phenomenon, curricular intensity. Two other circles, one for GPA and one for prior math scores, overlap with the circle for curricular intensity to represent the amount of curricular intensity that they explain. They overlap with each other to the extent that they measure the same construct. They all likely overlap in their measurement of content mastery and academic excellence. However, GPA also captures student behavior, which influences student performance (Lyons & Bandura, 2017) and soft skills such as self-control (Duckworth, Quinn, & Tsukayama, 2012). Prior test scores not only measure prior education and relevant academic training but is also commonly thought to measure native ability or aptitude (Gallagher & De Lisi, 1994). The visualization of this Venn diagram for curricular intensity, GPA, and prior math scores is shown in Figure 2.1.

Figure 2.1.

Venn diagram of connections (relationships) of curricular intensity, prior math scores, and GPA



In Figure 2.1, there is a portion of the curricular intensity circle that is *not* explained by either GPA or prior math test scores. In this study, I am asking: What remains in curricular intensity that is not captured in GPA and test scores? For example: What would explain differences of academic rigor, as measured by curricular intensity, between two students who share the same content mastery, behavior, self-control, and ability? One answer could be some unobservable internal ambition or engagement—manifested in the degree to which a student does or does not push himself into additional academic rigor.

The portion of the circle for curricular intensity in Figure 2.1 that does not overlap with the other two may represent the academic course quantity and quality that is due, at least in part, to students' ambition and engagement.

The Venn diagram represents a simple way to begin thinking about how constructs overlap and how the adjustment variables can explain curricular intensity, but it has limitations. The center of the diagram, where all three overlap, has meaning because it is the portion of curricular intensity that is explained by both GPA and prior test scores. But it is difficult to know its size because a correlation is, by definition, between two constructs and cannot capture the relationship between all three. To understand the size of the shared portion, and more importantly, the amount of curricular intensity that is left unexplained by the adjustment variables, a multivariate model must be estimated, as is found below.

By estimating a multivariate model, more than two adjustment variables can be included. I include SES and race as mentioned earlier. Aside from engagement or ambition levels, what would explain differences of curricular intensity between two students with the same GPA, same prior math scores, same SES level, and same race? One difference is opportunity; students attend different schools, which can differ in their course offerings (Oakes, 1985), but differences in opportunity for coursework can differ even within the same school. This within-school difference in opportunity begins with middle school coursework. Enrolling in lower-level middle school math courses has a limiting and rolling effect on what courses the student may access in high school. This pattern primarily disadvantages racial minority students and low-SES students (Attewell & Domina, 2008; Coleman et al., 1966; Domina, Hanselman, Hwang, & McEachin, 2016).In this study, curricular intensity—after adjusting for GPA, prior math scores taken in the fall of 9th grade, race, and SES—is a measure of academic course taking rigor that is due both structural opportunity as well as engagement and ambition. A limitation of this interpretation is that both structural opportunity and engagement or ambition are latent and, cannot be empirically confirmed.

CTE concentrator. The second element that needs to be measured after curricular intensity is the extent of a student's participation in CTE. Participation in CTE is most commonly defined by government (Levesque & Hudson, 2003; Silverberg et al., 2004) and researchers (Plank, 2001; Dougherty, 2016) alike as concentration in CTE. The manner in which the term "concentration" has been operationalized in extant research is commonly defined as enrolling in 3.0 Carnegie credits of CTE courses within the same career cluster. However, because multiple pathways exist within each career cluster, this operationalization leaves ambiguity about what students actually completed when they concentrate in CTE, and if it was meaningful.

In this study, I introduce a way to reduce the heterogeneity of qualifying course combinations, thereby reducing the ambiguity about the student experience and improving my ability to interpret the meaning of CTE participation. Specifically, I only count CTE courses that are non-duplicative and which count towards a program of study. In order to better allow others to follow or subsequently improve on my method, I will provide a robust description of how I connected courses to programs of study.

Although programs of study vary by school, I use sample programs of study provided by state CTE leaders from all 50 states (Advance CTE, n.d.). In so doing, I create a new measurement of student participation within a program of study using nationally representative data. This represents a more accurate measurement of CTE as it was designed in the Perkins IV reauthorization wherein programs of study were incorporated as a central feature of CTE (Stipanovic, Lewis, & Stringfield, 2012).

I accomplish this by drawing on the sample guide of programs of study that Advance CTE makes widely available (Advance CTE, n.d.). In the guide, a sample program of study is offered for each of the 79 programs of study, which are housed within 16 career clusters. The sample programs of study identify a set of courses that could comprise a general program of study for that pathway. For example, the guide recommends that students interested in the agribusiness pathway should take the following courses: an introduction to agriculture, agricultural marketing, agricultural business management, agricultural economics, and an internship in agribusiness. Advance CTE provides a course description for each suggested course. For a more complete example, see Table 2.1, which presents all of the sample pathways from the Agriculture, Food, and Natural Resources career cluster, as offered by Advance CTE.

These sample pathways are useful as a framework, but are made useful in analysis only by assigning a national course number to each course listed. To do this I draw on a national registry of all high school courses, known as the school course for the exchange of data (SCED) registry. All high school courses are intended by the SCED system to be categorizable within its numerical registry. SCED codes were chosen because they represent a national coding system and also because all HSLS:09 courses have a SCED code attached to them.

Both the documents from Advance CTE and SCED include recommended course titles and course descriptions. By comparing these documents, I attached a SCED code to each course listed in Advance CTE's sample program of study documents. After attaching SCED codes to each of the 79 programs of study I then calculated each student's progress within them.

Table 2.1

Courses Required Within the Programs of Study on Pathways Belonging to the ***Agriculture, Food & Natural Resource*** *Career Cluster*

Pathway	Course 1	Course 2	Course 3	Course 4	Course 5	Course 6	Course 7
Agribusiness Systems	Introduction to Agriculture, Food and Natural Resources	Introduction to Agricultural Marketing, Business and Entrepreneurship	Accounting	Agricultural Business Management	Agricultural Economics	Internship in Agribusiness	
Animal Systems	Introduction to Agriculture, Food and Natural Resources	Introduction to Animal Science	Advanced Animal Science	Small Animal Specialization	Equine Science	Biotechnology and Agricultural Science Research	
Environmental Service Systems	Introduction to Agriculture, Food and Natural Resources	Introduction to Environmental Service Systems	Power Systems	Research in Natural Resources and Biotechnology	Internship in Environmental Service Systems		
Food Products & Processing Systems	Introduction to Agriculture, Food and Natural Resources	Introduction to Food Products and Processing Systems	Advanced Food Products and Processing Systems	Agricultural Economics	Internship in Food Products and Food Processing Systems		

Table 2.1 (Continued)

Natural Resources Systems	Introduction to Agriculture, Food and Natural Resources	Introduction to Natural Resources and the Environment	Advanced Natural Resources and Environmental Systems	Research in Natural Resources and Biotechnology	Internship in Natural Resources		
Plant Systems	Introduction to Agriculture, Food and Natural Resources	Introduction to Plant and Soil Science	Advanced Plant and Soil Science focusing on agronomy, forestry and range science or horticulture	Biotechnology and Agricultural Science Research	Agronomy	Forestry and Range Science	Horticulture
Power, Structural & Technical Systems	Introduction to Agriculture, Food and Natural Resources	Introduction to Power, Structural and Technical Systems	Structural Systems	Power Systems	Internship in Power, Structural and Technical Systems		

Note. Bolded indicates Career Cluster. Underlined indicates a pathway.

A number of decisions had to be made in this process. Some schools offer two different courses—represented by two different course names, but attributed both to the same SCED code. For example, a school could give yearbook 1 and yearbook 2 the same SCED code that references yearbook courses, generally. In instances where a student took two courses that shared the same SCED code but distinct course names, two courses were counted as having been taken in pursuit of the associated CTE pathway.

There were seven courses suggested in programs of study by Advance CTE that were shared by pathways in more than one career cluster. In these cases, the courses were assigned a "home" career cluster, and students taking multiple, distinct courses sharing that course code were only counted once toward any non-home career cluster that used its course code. A course's home cluster was determined with best judgment after consulting career clusters and their targeted careers. For example, accounting is in the finance career cluster in the accounting pathway and also in the business management and administration career cluster. In this instance, accounting's home was decided to be in the finance career cluster because a specific accounting pathway resides within finance. A full list of courses shared by more than one career cluster and their home career clusters is given in Table 2.2.

Using Advance CTE's sample programs of study to determine CTE participation does have limitations. The programs of study used do not necessarily represent the true program of study that any student was following. As such it may capture students who were not intentionally taking connected courses or intending to pursue a career associated with the pathway I assigned them. However, although it may not be a perfect measure of any specific student's progress in a program of study, it does allow for the identification of courses that can appropriately be linked together into groups of classes that form meaningful experiences within CTE, as programs of study are designed to do.

Another limitation is that nine of the 79 programs of study are not completely built out by the guiding sample document. In each of these instances there is enough information provided to allow me to approximate what the courses would be. I address this limitation in the following way: I measure student participation at the program of study level in order to retain the advantages of measuring participation through programs of study, but for my analysis I roll the student's program of study up into the coarser career cluster level. This means that instead of showing CTE participation in the 79 programs of study where their participation was measured, I show CTE participation in the 16 career clusters.

This decision results in lost variation but increases validity of measurement while also increasing statistical power. When students qualify for more than one career cluster, I assign them to the career cluster associated with the program of study in which they completed the greatest number of courses. In the event of a tie, I randomize their assignment between the tied career clusters.

Another limitation of this use of programs of study is that the Advance CTE documentation indicates that the majority of programs of study should include a course in basic computer applications. As such, when a student completes a course in basic computer applications—and more than 7,000 of all students with transcripts do because many states allow it to satisfy graduation requirements in core subjects (Zinth, 2018)—they have one course completed in several programs of study.

Table 2.2

Home Career Cluster Assignments for Courses Found in Multiple Career Clusters

Course SCED Code	Course name	"Home" Cluster	Other Clusters Using
10004	Computer Applications	Information Technology	Architecture & Construction Arts, A/V Technology & Communications Education & Training Finance Government & Public Administration Health Science Hospitality & Tourism Human Services Law, Public Safety, Corrections & Security Manufacturing Marketing STEM Transportation, Distribution & Logistics
10005	Business Computer Applications	Business Management & Administration	Architecture & Construction Arts, A/V Technology & Communications Education & Training Finance Government & Public Administration Health Science Hospitality & Tourism Human Services Law, Public Safety, Corrections & Security Manufacturing Marketing STEM Transportation, Distribution & Logistics
12104	Accounting	Finance	Agriculture, Food & Natural Resources Business Management & Administration Government & Public Administration
12001	Business/Office Career Exploration	Business Management & Administration	Marketing
12052	Business Management	Business Management & Administration	Finance Hospitality & Tourism Human Services Law, Public Safety, Corrections & Security
12109	Income Tax Accounting	Finance	Government & Public Administration
21012	Civil Engineering and Architecture	STEM	Architecture & Construction

Although it is customary in CTE research to define CTE concentration as outlined above—3.0 of any Carnegie units within a career cluster, this definition may be shifting. Federal funding for CTE was recently re-legislated in 2018 in a bill commonly known as Perkins V. This new legislation did not significantly alter the design of CTE, but it did provide the first formal measurement of how to measure a concentrator (Advance CTE, 2018). Under the new definition of concentrator, non-duplicative courses within a program of study are counted instead of credits within a career cluster. Under Perkins V, the threshold for concentration is placed at two courses (Advance CTE, 2018). Under this definition, the 7,000 students in my sample who completed an introductory computer course would be one course away from completing a concentration in CTE. To address this limitation, I adopt a more conservative version of the Perkins V concentrator definition by requiring one additional course: where Perkins V requires two completed, non-duplicative courses in a program or program of study, I require three completed, non-duplicative courses in a program of study.

Using this definition, I find that 21% of the students in my sample meet my definition of CTE participation within a program of study with every career cluster populated by an average of 138 students, as seen in Table 2.3. Although there is no way to know what percentage of students actually met my definition of CTE participation within the real programs of study at their schools, an informed judgment can be made by comparing to a coarser, known number. That is, nationally 39% of students earn three or more CTE credits total, summing across all career clusters (NCES, 2009). This percentage is likely higher than mine because it allows any course within a career cluster to count towards the three-credit total—including unrelated or duplicate courses. Therefore, I judge that 21% of students meeting my criteria is a reasonable approximation for the number of students who meet my conservative definition.

Table 2.3

Sample Size by CTE Career Cluster

Career Cluster	N	Not missing any covariate.
No CTE	7,440	6,810
Agriculture	120	110
Architecture & Construction	210	190
Arts & Communication	490	450
Business Management	90	80
Education & Training	140	140
Finances	130	120
Government & Administration	130	120
Health Sciences	170	160
Hospitality & Tourism	90	80
Human Services	20	20
Information Technology	70	60
Law, Corrections, & Security	40	40
Manufacturing	40	40
Marketing	60	50
STEM	120	110
Transportation	110	110
All Students	9,460	8,680

Note. All sample sizes rounded to the nearest 10, in accordance with guidelines for the use of restricted NCES data.

Analytic Approach

I first establish the relationship between curricular intensity and the adjustment variables to enable the interpretation of curricular intensity for subsequent analyses, as discussed above. To do this I regress curricular intensity on the adjustment variables in an ordinary least squares model:

$$currint = \beta_0 + \beta_1 GPA + \beta_2 Math\ Score + \beta_3 Race + \beta_4 SES + \varepsilon_i \quad (1)$$

where β_0 represents the curricular intensity for a White student of average SES, and an average Math Score, but with a GPA of zero. The constant will not be interpreted for the magnitude of its value but only for its significance. If the constant is significant after adjusting for GPA, math score, race, and SES, then curricular intensity is not entirely explained by them. It would then represent a portion of students' curricular intensity that is otherwise unexplained except by, perhaps, the factors previously discussed above. After conducting this analysis with all students, I repeat the analysis for CTE students and non-CTE students to determine if the finding holds for both groups.

I then proceed to examine the extent to which tracking may still be present in schools. Under the changes to public schools that removed formal tracking into or out of CTE, a student's level of curricular intensity should no longer be a significant predictor of participation in CTE. To determine whether and what differences exist between students participating in CTE and students not participating in CTE, I compare the levels of curricular intensity using a t-test as follows:

$$t = \frac{Curricular\ Intensity_{non-CTE} - \ Curricular\ Intensity_{CTE}}{sd_{curricular\ intensity}} \tag{2}$$

A significant *t* statistic would indicate that there are differences in the level of curricular intensity between CTE students and non-CTE students. In the era of tracking and vocational education, the difference between these two groups was significant and meaningfully large. If the current era of no tracking and encouraging all students towards both academics and CTE is successful in its design, then there would no meaningful difference between the two groups. Academically inclined students would participate in CTE and students inclined towards CTE would still participate in rigorous academics. I also provide a descriptive boxplot of the distributions of curricular intensity for both CTE and non-CTE students in Figure 2.2.

I next replicate the t-test in an ordinary least squares regression framework to allow for the inclusion of my adjustment variables. This allows for a repeated and more rigorous test of the same question to determine whether differences in curricular intensity levels exist between CTE and non-CTE students, but after adjusting for variables known to correlate with tracking.

I then follow with an ordinary least squares regression that allows for the comparison of curricular intensity values of all 16 career clusters and non-CTE students simultaneously as follows:

$$\begin{aligned} currint = {} & \beta_0 + \beta_1 Agriculture + \beta_2 Architecture\&Construction + \beta_3 Communications \\ & + \beta_4 BusinessManagement + \beta_5 Education + \beta_6 Finances \\ & + \beta_7 Government\&Administration + \beta_8 HealthSciences \\ & + \beta_9 Hospitality\&Tourism + \beta_{10} HumanServices \\ & + \beta_{11} InformationTechnology + \beta_{12} LawCorrections\&Security \\ & + \beta_{13} Manufacturing + \beta_{14} Marketing + \beta_{15} STEM + \beta_{16} Transportation \\ & + \varepsilon_i \end{aligned} \tag{3}$$

where β_0 represents the level of curricular intensity of non-CTE students and $\beta_1 \ldots \beta_{16}$ represent the difference in curricular intensity for students in each career cluster as compared with non-CTE students. If tracking within CTE is not occurring, then the global *F*-test will be statistically insignificant and individual career clusters will not have significantly different levels of curricular intensity from non-CTE students. If tracking is occurring inside of CTE, then the opposite will be true—the global *F*-test will be statistically significant and differences between CTE career clusters and non-CTE students will be significant. I also produce a descriptive boxplot showing the distribution of each CTE career cluster and non-CTE students in Figure 2.3.

I then repeat this analysis with adjustment variables included. If a significant *F*-test remains after adjusting for the known correlates of tracking, then it provides evidence of possible structural inequity occurring within CTE between its career clusters. It could also indicate that some career clusters attract students with higher or lower levels of ambition compared to their peers. It will certainly indicate that sorting within CTE by academic course schedule is occurring in public schools nationally.

This approach to determine whether students in rigorous academic courses are participating in different areas of CTE is preferred to other approaches because it allows curricular intensity to remain on a continuous scale. It also builds on established constructs that have been used and respected as appropriate ways for measuring tracking and place within school performance hierarchy (Gamoran & Mare, 1989; Lucas, 1999). Therefore, this approach is preferred to other methods such as cluster analysis, which definitively categorizes students as belonging to specific groupings known as clusters. Because rigid tracks are no longer used in schools, a discrete categorization of differences in curricular experiences—real though they may be—is not as elegant a solution or as representative of students' lived experiences as is a continuous measure of curricular intensity. For completeness of inquiry, a cluster analysis was conducted, but substantive results did not differ from results reported below and provided coarser information.

Results

Before interpreting curricular intensity, I explored the relationship between it and other variables known to correlate with historical tracking practices. Because these variables have been shown to predict students' track placement as well as participation in CTE, there is an open question as to whether curricular intensity would be entirely explained by them. Table 2.4 presents the estimates of the relationship between curricular intensity and GPA, prior math test score, SES, and race.

Each of the included variables is significantly associated with curricular intensity, which indicates that they each predict academic course taking quantity and quality. The constant is also significant, which indicates that curricular intensity is not entirely explained by the adjustment variables. It also indicates that after accounting for the adjustment variables, the constant still explains meaningful information about students' curricular intensity. The R^2 value indicates that nearly half of the variation in curricular intensity, 46%, is explained by the included variables, which leaves a substantial portion of student course taking as measured by curricular intensity unexplained. This indicates that other unmodeled factors contribute to observed academic course taking, such as structural opportunity and student ambition or engagement.

Table 2.4

Ordinary Least Squares Regression of Curricular Intensity on Constructs Known to Correlate with Historical Tracking Practices

	All Students	Non-CTE Students Only	CTE Students Only
Background			
Socioeconomic Status	0.26***	0.22***	0.42***
	(0.04)	(0.04)	(0.07)
Math Score	0.73***	0.76***	0.63***
	(0.05)	(0.05)	(0.06)
Race (reference category: White)			
Black	0.63***	0.59***	0.73***
	(0.10)	(0.12)	(0.19)
Asian	0.49***	0.49***	0.49**
	(0.11)	(0.13)	(0.17)
Hispanic	0.93***	0.90***	1.02***
	(0.15)	(0.17)	(0.19)
Other	0.16	0.17	0.08
	(0.09)	(0.10)	(0.14)
Schooling			
Cumulative GPA	1.14***	1.19***	0.87***
	(0.06)	(0.07)	(0.08)
Constant	1.75***	1.64***	2.47***
	(0.18)	(0.21)	(0.24)
F-Value	362.09***	323.93***	89.04***
Df	(7, 760)	(7, 750)	(7, 530)
R^2	0.46	0.47	0.41
N	8,680	6,810	1,870

I proceeded to determine what differences existed in curricular intensity levels between CTE and non-CTE students. The current narrative around CTE would suggest that it is designed to attract and serve all students equally. Table 2.5 indicates that the difference in curricular intensity between CTE students and non-CTE students is not significant (t = -0.77, p = 0.444), and the distribution of curricular intensity values is similar, as seen in Figure 2.2. This indicates that students participating in CTE do not have academic course schedules with lower quantity or of lower quality than their non-CTE peers.

Table 2.5

T-test of Mean Curricular Intensity Between Students Participating in CTE and Non-Participants

	Mean	SE	T	P
Non-CTE	5.28	0.08	-0.77	0.444
CTE	5.34	0.06		

Table 2.6

Ordinary Least Squares Linear Regression of Curricular Intensity on CTE Participation

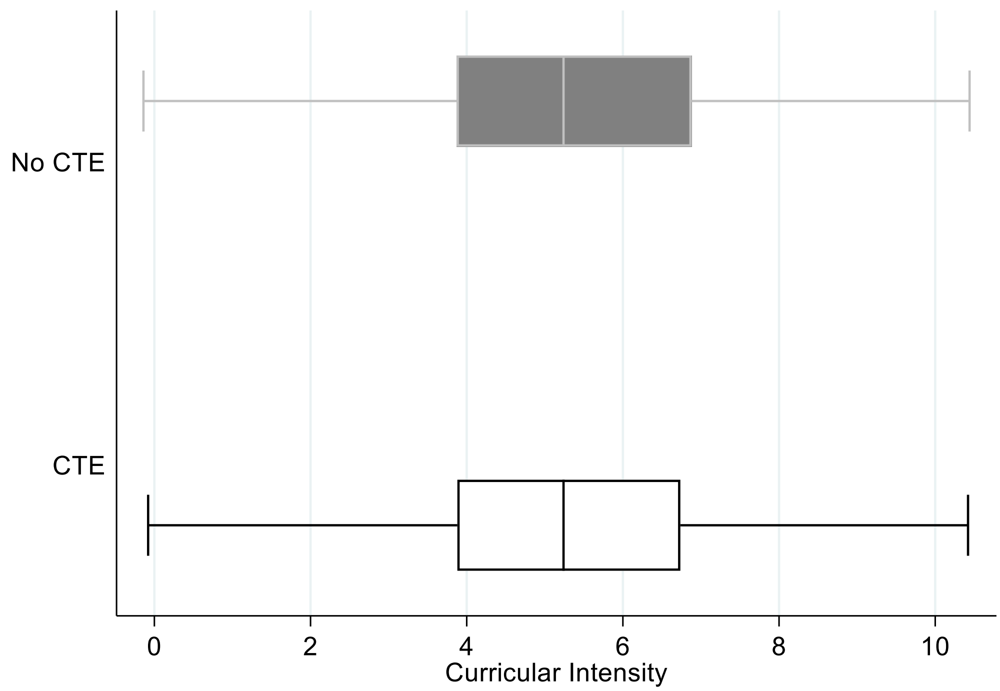
	Coefficient	SE	Coefficient	SE
CTE	-0.06	(0.08)	-0.09	(0.07)
GPA			1.14***	(0.06)
SES			0.26***	(0.04)
Prior Math			0.73***	(0.05)
Race				
Black			0.62***	(0.10)
Asian			0.49***	(0.11)
Hispanic			0.92***	(0.14)
Other			0.16	(0.09)
Constant	5.34***	(0.06)	1.77***	(0.18)
N	8,680		8,680	

I proceeded to conduct the same test in a regression analysis with adjustment variables. I found that the difference in curricular intensity levels between CTE and non-CTE students remained insignificant, even after adjusting for attributes that correlate with tracking, as seen in Table 2.6. This indicates that although students' academic curricular intensity remains associated with their math scores, race, SES, and GPA, it is not associated with their participation in CTE. In other words, I found no evidence of tracking into or out of CTE by academic credentials.

An analysis that stopped at this point would indicate that de-tracking has been successful. Students of every academic background are participating in CTE, and students who participate in CTE are not kept from participating in rigorous academic courses. However, this initial look at CTE aggregates all of the career clusters together. By breaking out each career cluster of CTE, as seen in Table 2.7, the results suggest that some tracking is occurring.

Figure 2.2

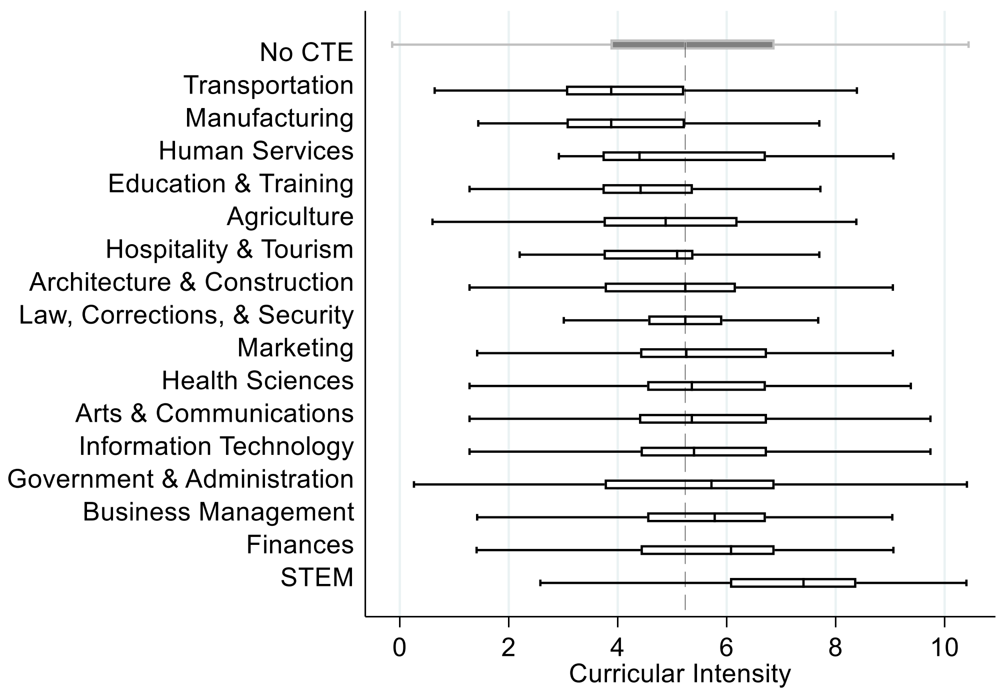
Curricular Intensity of Non-CTE and CTE High School Students



Note. Weights applied for nationally representative estimates.

The analysis produced a global F-value (16, 760) of 10.20, which is significant at the $p < 0.001$ level. This indicates that there are significant differences between the compared groups, which included all 16 career clusters as well as the non-CTE group. Comparing each group to the non-CTE group as the reference category indicated that students in the Education and Training, Hospitality and Tourism, Manufacturing, and Transportation career clusters all had significantly lower levels of curricular intensity in their academic coursework than non-CTE students. After adjusting for GPA, math score, SES, and race there was still a significantly lower curricular intensity for students in Education and Training and Transportation—although the magnitude of the relationship is reduced. Somewhat surprisingly, the coefficient for students in Finance flipped from an insignificant but positive association with curricular intensity to a significant and negative association with curricular intensity after including adjustment variables.

Figure 2.3
Curricular Intensity of Each CTE Career Cluster



Note. Weights applied for nationally representative estimate. The dashed vertical line aligns with the curricular intensity value of the median Non-CTE student.

In contrast, STEM is the only career cluster with a significantly higher level of curricular intensity than the average non-CTE student. The significant positive association between STEM and curricular intensity is not changed when adjustment variables are taken into account. This indicates that there may be more structural opportunity to participate in STEM at schools that have higher levels of curricular intensity, or that STEM may attract students with greater intrinsic ambition and engagement. The same finding holds when excluding non-CTE students and comparing only across career clusters.

These results collectively indicate that when grouping all of the career clusters together into a single group (i.e., CTE) in conversation or analysis, the full distribution of curricular intensity throughout CTE is more accurately represented. In other words, the practice of referencing CTE students as one monolithic group smooths over the variation of a heterogeneous group. And while each career cluster has its own range of curricular intensity, each tends to fall within a specific segment of the overall distribution, as seen in Figure 2.3. For example, students in the transportation career cluster tend towards a lower level of curricular intensity. Students from that cluster at the 75th quartile, who have a high level of curricular intensity relative to their transportation peers, are only high compared to those transportation peers. When compared to non-CTE students, they have an average level of curricular intensity overall, with 50% of the rest of the non-CTE students having a higher level of curricular intensity.

The R-squared value for the regression of curricular intensity on CTE clusters—including non-CTE as an option, is 0.02. This indicates that 2% of the variation between groups is explained by differences in curricular intensity. An R-squared value of this level is generally considered low. Its low value aligns with the narrative that the t-test supported—no difference between CTE and non-CTE students.

Table 2.7

Differences in Curricular Intensity Between CTE Career Clusters and Non-CTE Students

	All Students		CTE Students Only	
	(1)	(2)	(4)	(5)
Career Cluster				
Agriculture	-0.36	-0.36	-0.39	-0.20
	(0.30)	(0.26)	(0.31)	(0.27)
Architecture & Construction	-0.24	0.07	-0.27	0.14
	(0.17)	(0.13)	(0.20)	(0.14)
Arts & Communication	0.03	-.11		
	(0.11)	(0.09)		
Business Management	0.26	.23	0.23	0.35*
	(0.17)	(0.16)	(0.19)	(0.16)
Education & Training	-0.77**	-0.60**	-0.80**	-0.51*
	(0.23)	(0.22)	(0.25)	(0.23)
Finances	0.28	-0.48**	0.26	-0.24
	(0.25)	(0.18)	(0.27)	(0.19)
Government & Administration	0.10	-0.05	0.07	0.07
	(0.31)	(0.23)	(0.31)	(0.22)
Health Sciences	0.18	0.16	0.15	0.27
	(0.20)	(0.17)	(0.22)	(0.17)
Hospitality & Tourism	-0.54*	0.09	-0.57*	0.09
	(0.23)	(0.36)	(0.24)	(0.31)
Human Services	-0.19	-0.04	-0.22	0.03
	(0.40)	(0.31)	(0.41)	(0.31)
Information Technology	0.10	0.08	0.08	0.18
	(0.31)	(0.24)	(0.32)	(0.23)
Law, Corrections, & Security	-0.10	0.26	-0.13	0.29
	(0.31)	(0.16)	(0.27)	(0.17)
Manufacturing	-1.19***	-0.58	-1.22***	-0.61*
	(0.28)	(0.30)	(0.29)	(0.30)
Marketing	0.08	-0.18	0.06	-0.05
	(0.24)	(0.22)	(0.25)	(0.22)
STEM	1.69***	0.60***	1.67***	0.84***
	(0.19)	(0.12)	(0.21)	(0.13)
Transportation	-1.19***	-0.39*	-1.22***	-0.41*
	(0.23)	(0.19)	(0.24)	(0.21)
Adjustment Variables	No	Yes	No	Yes
Constant	5.34***	1.76***	5.37***	2.49***
	(0.06)	(0.18)	(0.10)	(0.26)
F Value	10.20***	123.00***	10.79***	46.51***
Df	(16, 760)	(23, 760)	(15, 530)	(22, 530)
R^2	0.02	0.46	0.11	0.44
N	8,680	8,680	1,870	1,870

Note. * significant at p <0.001 level. ** significant at p <0.01 level. * significant at p <0.05 level. Sampling weights applied for nationally representative results. In models 1 – 2, the constant is the non-CTE group. In models 3 – 4, the constant is the arts & communications cluster (chosen for its large sample size). Adjustment variables include GPA, 9th grade math score, SES, and race.

The same R-squared statistic jumps up to 0.11 when omitting non-CTE students. This means that 11% of the differences in the quantity and quality of academic coursework can be explained by the career cluster that students belong to. This does not represent stark divides between career clusters in the way that past tracking practices differentiated between academic and vocational students. However, it does indicate that there are clear associations between the CTE career clusters students participate in and their academic course taking.

Discussion

The results suggest that there are differences of curricular intensity within CTE, by career cluster. Career clusters that emphasize technology or lead to prestigious professions are populated by students with higher levels of curricular intensity. Meanwhile, there are several CTE clusters that attract students with lower academic profiles, similar to vocational education. The 11% of differences in curricular intensity that is explained by CTE career clusters may actually be an underestimate. Due to the limitation of curricular intensity as a counting variable, the study sample only includes successful (graduating in 4 years) students. It is possible, and indeed likely, that the 16 career clusters would fill disproportionately with students who take longer to graduate. The effect of this on the present analysis is to raise the mean level of curricular intensity for all affected career clusters by excluding those would be mostly at low levels of curricular intensity.

The finding of some sorting within CTE suggests that some career clusters of CTE, or pathways within career clusters, may operate similarly to vocational education several decades ago. A visitor to a school's auto shop class in the 1980s may have found roughly the same type of students as he would find when visiting a school's current day auto shop class, which is within the transportation career cluster. This career cluster attracts primarily non-college bound students who are likely from low-SES families. This inference is supported by the established relationship between low levels of curricular intensity and low college enrollment (Austin, 2020).

Sorting patterns similar to vocational education do not occur in all career clusters, but it does appear to occur in the career clusters associated with the lowest paying industries. This is potentially problematic because it is occurring in tandem with differences in opportunity. Many students from a low-SES or racial minority backgrounds do not have the same opportunities academically as more advantaged students and may be doubling down on the lack of opportunity by enrolling in career clusters that lead to immediate employment in potentially lower-paying careers.

The finding of inequitable sorting within CTE is troubling. CTE courses available in most American public high schools are intended to prepare all students for college or careers and benefit student earnings. CTE is seen as a way for students to "get ahead" while they are still in high school. It is intended to allow students from low-SES households to obtain marketable skills for high earnings prospects. Instead, student participation in some CTE career clusters largely follows the sorting pattern that has been in place for generations: students from economically disadvantaged backgrounds exhibit course enrollment patterns that are unlikely to help them increase their upward mobility. The difference is that now, instead of sorting into or out of CTE, students are sorting within CTE.

There are, potentially, varied reasons for these enrollment patterns under the current organization of CTE. Future research into the most critical questions is needed. New studies may begin by investigating if and how differences exist in the CTE options that are presented to students. To what extent do course offerings differ by school? Do students of all academic backgrounds receive equal information from school counselors about the available CTE options? It is possible that the structural opportunities surrounding, supporting, and gatekeeping CTE are not equal for all students.

More explicit inquiry into the differences of structural equality within CTE is recommended as an important line of research to address in the future. Structural inequality within CTE may be complicated by the high cost and unique space requirements for various CTE career clusters. For example, career clusters that heavily incorporate computer-based technology may fit into any classroom at a school. Square footage of the classroom is not as much of an obstacle as is having enough money to pay for costly supplies like robot kits, cameras, or software licenses. Older schools in existing under-resourced communities, such as inner cities or rural areas, may have older school buildings with layouts that include large shops for machinery-based technology for traditional trades. These career clusters require high amounts of square footage, often prevalent in older buildings, and can frequently use decades-old shop machines that still function. This scenario may be especially prevalent in cities with a rich history of manufacturing, but which have lost funds and reduced populations of families as manufacturing has been outsourced, leaving shrinking communities unable to build new school buildings.

Understanding more about the sorting processes that this study discovered is important for addressing underlying issues of equality. School leaders and planners should not simply be satisfied by the presence of CTE courses in schools, but work to ensure that the offerings are thoughtfully chosen so as to increase opportunity for students while also aligning with the local labor market demand. This may include difficult questions about whether to build up existing offerings or target new CTE pathways that better serve students. The findings of this study should benefit future CTE research by suggesting that it is important to account for curricular intensity and various career clusters. A student's academic curriculum should be an important consideration in future CTE research.

Without accounting for students' curricular intensity, current CTE research is estimating the effects of CTE on outcomes such as college enrollment and graduation (Gottfried & Plasman, 2018; Giani, 2017) without accounting for the differences between the career clusters.

Ignoring differences and sorting within CTE results in inaccurate perceptions and uninformed decisions. Currently CTE enjoys an improved reputation as school counselors have shown increasing willingness to counsel students into CTE (Coleman, 2018). This feeds the narrative that CTE is entirely changed from its days as vocational education and is unrelated to tracking practices that route disadvantaged students towards non-college, low-paying careers.

Ignoring this narrative may have real consequences for today's students who do feel limited in their options. Children were affected decades ago when tracking was hiding in plain sight. Without additional attention to the barriers to equity within CTE, policymakers who advocate for CTE in its current implementation may be unwittingly advocating for the perpetuation of a more subtle form of modern-day tracking—within-CTE.

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Chapter III

High School Dropout and CTE: A Difference of Curricular Intensity

Introduction

Participation in high school career and technical education (CTE) has consistently been shown to reduce the probability of high school students dropping out (Gottfried & Plasman, 2018; Neild, Boccunfuso, & Byrnes, 2015; Plank, 2001; Plank, DeLuca, & Estacion, 2008). This effect is most pronounced among low-income students (Dougherty, 2016). Several mechanisms have been offered as reasons that CTE may reduce dropout, spanning from increased motivation (Gottfried & Plasman, 2018), finding a smaller community within a school (Kemple & Willner, 2008), or fostering a personal identity that includes school participation (DeLuca, Clampet-Lundquist, & Edin, 2016). Although each of those mechanisms is distinct, I will discuss them collectively as mechanisms through which CTE may re-engage disengaged students.

Students who disengage and subsequently drop out come from all backgrounds and aptitude levels. For some disengaged students who drop out, their performance and tested aptitude is perpetually low; other disengaged students display high aptitude but low performance because of disinterest or boredom (Bowers & Sprott, 2012; Kronick & Hargis, 1998). But disengagement is not static—many students begin high school engaged and disengage during high school (Finn & Zimmer, 2012).

Regardless of the path to disengagement, CTE is believed to be an effective mechanism for engaging or re-engaging students, thereby reducing dropout levels and increasing persistence to graduation (Stone & Alfeld, 2004). However, academic and policy discussions around CTE and dropout have skipped from offering CTE to improving dropout rates without fully considering the engagement mechanism that connects the two. Discussions have either focused on the benefits of CTE for all students (Gottfried & Plasman, 2018) or on the greater benefit for low-income students (Dougherty, 2018). The observed benefit of CTE against dropout for low-income students may have more to do with the low levels of engagement found amount low-income students (Smith, Brooks-Gunn, Klebanov, 1997) than it does with their income.

The constructs of engagement, academic performance, and dropout are correlated with each other and with a student's family income (Alexander, Entwisle, & Kabbani, 2001; Bowers & Sprott, 2012; Hauser, Simmons, & Pager, 2000). Low-income students have consistently higher rates of dropping out of high school as well as lower levels of academic performance and engagement (Balfanz, Bridgeland, Moor, & Fox, 2010). These associations have been stable over time and resistant to change efforts (Hauser, Simmons, & Pager, 2000). The close association between them may allow for a case of mistaken identity when determining which students benefit the most from reduced dropout rates after CTE participation. It may be that disengaged students may benefit more from CTE than low-income students.

In order to investigate this, I will leverage a recent refinement (Austin, 2020) to an established tool known as curricular intensity (Adelman, 1999, 2006) to isolate student engagement from family income. Curricular intensity measures the quantity and quality of courses students take, which are both strong predictors of engagement and graduation from high school or eventual dropout (Adelman, 2006; Bowers & Sprott, 2012).

The planned analyses will promote a more informed discussion of the potential for CTE to reduce dropout for disengaged students or for low-income students. If low-income students benefit more from CTE than disengaged students, then the mechanism long assumed to drive CTE students' reduced dropout rate may need to be reevaluated. Conversely, if disengaged students benefit more from CTE than low-income students, then recommendations for policy implementation and guidance counselors may shift accordingly.

In this paper, I will present a review of the literature, expanding on elements introduced briefly above. Then, I present a description of my data and sample, and how I account for changes in students' level of engagement from year to year. After sharing my findings, I discuss the implications of this study for future research and policy.

Literature Review

The academic literature on CTE largely supports the belief that students who participate in CTE are less likely to drop out of high school (Gottfried & Plasman, 2018; Neild, Boccunfuso, & Byrnes, 2015; Plank, 2001; Plank et al., 2008). This is the most common finding, although a few have reported CTE increasing dropout (Ainsworth & Roscigno, 2005) or null associations (Agodini & Deke, 2004) between CTE participation and high school dropout.

The first causal study conducted in CTE, a randomized experiment of career academies, indicated participation in the career academy reduced dropout rates for students who were considered high-risk because of prior attendance rates, behavior, and academic performance (Kemple & Willner, 2008). Another study that conducted regression discontinuity analyses supported a similar conclusion—participation in CTE courses decreased dropout rates, and the effect was largest for low-income students (Dougherty, 2018).

The observed protective association of participating in CTE with high school graduation is often attributed to the re-engagement of students in school. It is assumed that students find that CTE courses provide them with increased autonomy and easily recognized real-world applications (Gentry, Peters, & Mann, 2007)—both components that increase motivation (Pintrich, 2003). Another reason that CTE may help increase engagement in school is because students often feel greater support and encouragement in smaller classes or small cohorts of students who remain together over several semesters or years, as they may do in CTE courses. The benefit of smaller learning communities within schools is that students may make stronger connections with teachers (Cotton, 2001). A formal example of small and close communities within schools is the use of career academies in which cohorts of students participate in the same courses over several years. Students who participate in career academies have lower dropout rates (Kemple & Willner, 2008). Also, CTE students may dropout at lower rates because they have found a personal identity centered in CTE (DeLuca, Clampet-Lundquist, & Edin, 2016; Finn & Zimmer, 2012). Students from families with low income may not have strong educational support at home. They may benefit from the structured and reliable structure that CTE offers for them to connect with stable adults, peers, and interests (DeLuca et al., 2016).

All of these mechanisms may help students make the decision to persist in high school. This is consistent with self-determination theory that indicates that individuals' intrinsic motivation in making decisions is influenced by feelings of competence, autonomy, and relatedness (Deci & Ryan, 2000; Ryan & Deci, 2000). When students experience those factors, which are all noted strengths of CTE (Gentry, Peters, & Mann, 2007), they may be more motivated to learn (Pintrich, 2003), more engaged in learning (Van Ryzin, 2011), and disinclined to drop out (Archambault, Janosz, Fallu, & Pagani, 2009). The mechanism of reengaging students through a substantially different and engaging learning environment has commonly been cited to explain the observed relationship of lowered dropout rates and CTE (Alfeld, Hansen, Aragon, & Stone, 2006; Gentry, Peters, & Mann, 2007; Gottfried & Plasman, 2018).

The need for re-engagement may come at different points in time depending on the student. Eventual dropouts who may struggle with engagement from the outset of high school include those with historic patterns of low achievement who continued to perform poorly in school, making engagement in and optimism about school difficult (Janosz, LeBlanc, Boulerice, & Tremblay, 2000; Kronick & Hargis, 1998; Lessard, Butler-Kisber, Fortin, Marcotte, Potvin, & Royer, 2008). Sometimes disengagement may not be due to learning difficulties, but boredom with school—a pattern seen in students with high academic ability who disengage (Kronick & Hargis, 1998). The largest group of dropouts are those who rapidly disengage when outside obstacles arise and they do not have the support they need outside of school to be successful in school (Bowers & Sprott, 2012; Menzer & Hampel, 2009). Although timing and reasoning for a student's disengagement vary, students who disengage display a similar pattern of accruing a lower quantity and quality of academic coursework. They drop out of school at higher rates (Bowers & Sprott, 2012).

Although re-engagement for disengaged students is often discussed in research on CTE and dropout rates, a measure of engagement has not been modeled in extant studies. The literature discusses engagement but does not clearly identify which students would benefit most from CTE. Most research has focused on reporting the relationship between CTE and the prevention or reduction of dropping out as it is observed for all students, on average (Plank, 2001; Gottfried & Plasman, 2018). The two causal analyses that were conducted are exceptions. The first indicated that although all students, on average, see increased protection against dropping out, low-income students are more strongly protected than other students (Dougherty, 2018). The other causal study indicated that participation in CTE through career academies decreased the probability of dropping out in largest measure for students who were classified as high risk based on background characteristics (Kemple & Willner, 2008).

The information lost by focusing only on student background characteristics is potentially impactful. Stakeholders believe that CTE increases engagement (Grams, 2014; Stone & Alfeld, 2004), but most prior analyses and discussions focused on student background variables instead of on those who needed extra attention to become positively engaged in school. The result is that disengaged students from mid- to high-SES families or students who were high-achievers prior to high school are not considered when discussing for whom CTE may have protective impact. Focusing on background characteristics that correlate with engagement leads to relevant discussions, but may miss the mark. If school counselors focus on benefits of CTE for low-income students, they may miss opportunities to consider which disengaged students would benefit from CTE, irrespective of personal background.

The difficulty in conducting research on students' level of engagement is that it is difficult to measure, and may be treated as a latent and unobservable measure. However, it does manifest in directly observable behavior when leading to dropout: students who disengage socially, cognitively, or academically struggle in complex subjects such as math (Finn & Zimmer, 2012). They invest less time and effort in their course work and accrue fewer overall credits (Bowers & Sprott, 2012; Balfanz et al., 2010).

A recent refinement on an established instrument allows for a single measurement that aligns with these indicators of disengagement. The instrument, known as curricular intensity, is transcript based and captures both the quantity and quality of academic credits earned. The original instrument combined 13 values summarizing course taking in an objective measurement of the intensity of a student's academic experience (Adelman 1999; Adelman 2006). The original curricular intensity measure developed by Adelman has been widely used to account for student curricular experiences (An, 2013; Bound, Lovenheim, & Turner, 2010; Bozick & DeLuca, 2005; Carnevale, Smith, & Strohl, 2010; Niu & Tienda, 2013).

The recent refinement (Austin, 2020) simplifies the original instrument to require only four values. The refinement retains the objective accuracy in measuring curricular experiences that the larger original instrument developed and may even slightly outperform the original instrument (Austin, 2020). Curricular intensity is a closer proxy for student engagement than background characteristics because it measures observable course taking behavior that correlates with success or failure in school (Bowers & Sprott, 2012). Its use will allow for an improved analysis about this the impact of CTE on dropout.

The level of math that a student has achieved year to year may also serve as a proxy for engagement because increasingly difficult math courses include complex ideas that disengaged students may be less inclined to expend effort on. The level of math that a student has achieved is consistently the largest contributor to the value of a student's level of curricular intensity (Austin, 2020). Both curricular intensity and level of math may be seen as proxies for engagement in answering questions of who benefits most from CTE's protective effect.

However, curricular intensity and level of math are imperfect measures of engagement because they are confounded with other factors that influence course-taking patterns. Several of the confounding elements can be addressed by including appropriate adjustments, as discussed below, but it is unlikely that all confounds are accounted for. The difficulty of directly measuring engagement renders me unable to determine exactly how much my measure of curricular intensity and math level truly represent engagement after adjusting for known confounders. I proceed with the understanding that curricular intensity and math level are useful constructs that include student engagement as a prominent component after adjusting for known confounders.

Method

Data and Sample

To compare the association between CTE and dropout for both low-income and disengaged students, I use the *High School Longitudinal Study* of 2009 (HSLS:09) collected by the National Center for Education Statistics (NCES) at the U.S. Department of Education. This dataset followed a sample of students who were enrolled in ninth grade during the base year of 2009-2010. The sampling of students in the ninth grade makes this an appropriate dataset for questions of dropout because many dropouts are not promoted beyond the 9th grade (McCallumore & Sparapani, 2010).

The base-year data was collected in the fall of 2009, and follow-ups were conducted in the spring of 2012, and again in the fall of 2013 (i.e., a few months after most of the cohort graduated from high school). A second follow-up occurred in 2016, and a third follow-up is planned for 2025. Transcript data were reported by each student's school. Data on students' social background were collected on a parent questionnaire in the base year, the fall of 2009. Students were given a computer-adaptive algebraic assessment in the base year (2009) and in the first follow-up (2012).

In order to appropriately answer the research question and handle missing data, I will construct three samples from the data, as explained in detail below. For each of the three samples, I restrict my analytic sample to the public high school students who were first-time 9th graders in 2009-2010 at a school where CTE was offered and who have a transcript on file.

Measures

Independent variables. I measure participation in CTE as the number of distinct courses students enroll in within a program of study. A program of study is a set of cohesive courses that progressively intensify and deliver technical skills to a student for a designated career (Threeton, 2007). Measuring participation within a program of study is preferred to the measurement of CTE as a simple accumulation of all CTE courses for several reasons. Measuring participation in programs of study is a better representation of CTE because the design of CTE encourages participation through programs of study (Threeton, 2007). Additionally, participation in a program of study is more meaningful than a simple measurement of accumulated, and possibly disconnected, CTE courses.

To measure student participation in programs of study, I count the number of relevant and distinct courses students completed (i.e., earned course credit). I specify relevant courses as those listed in the 79 programs of study compiled by a group of state CTE leaders from all 50 states (Advance CTE, n.d.). To accomplish this, I identify the appropriate course code for each course in a program of study. The course codes that I choose from are those found in the School Course for the Exchange of Data (SCED) index. SCED codes are provided in my dataset for all courses found in transcripts. Thus, SCED codes become the crosswalk between the documentation outlining 79 viable programs of study, and course taking of students in my dataset. For more details about the method for matching courses from programs of study to courses listed in transcripts, see Chapter II.

Students who took courses in any of the 79 programs of study were counted as having participated in that program of study. If students participated in multiple programs of study, the number of courses counted in their CTE progression were those from the program of study in which they had taken the greatest number of distinct courses. This measure of CTE progress relies on a national body's designation of how viable programs of study could be constituted for different careers. However, schools have the freedom to construct their own programs of study that they feel best prepare students for any given career. As such, my measure of student progress in a program of study should not be interpreted as students' progress in their school's specific program of study. Rather, the measure used in this study reflects students' participation in CTE courses in a valid program of study codified by Advance CTE.

I use two measures as proxies for engagement. The first is curricular intensity which is created using the number of English course credits each student earned, the number of lab science courses taken (i.e., biology, chemistry, physics), the highest math course taken, and whether any AP course was ever taken. These components are included in a confirmatory factor analysis (CFA) that computes the relative contribution of each component to the latent construct of curricular intensity. The standardized factor loadings that result from the CFA are used as scalars, multiplied respectively against the appropriate component value for each student. After multiplying, the products are summed to create a single numerical indicator of curricular intensity. The process is represented mathematically as follows:

$$curricular\ intensity = \lambda_1(highmath) + \lambda_2(english) + \lambda_3(coresci) + \lambda_4(AP)$$

where λ is the standardized factor loading of each variable on the latent curricular intensity indicator. I use the standardized factor loadings for HSLS:09 transcripts provided by Austin (2020), who provides convincing diagnostics that the loadings appropriately measure curricular quantity and quality.

To construct curricular intensity, each component must be measured from the students' transcripts, reflecting students' records of all courses completed through the high school years. Curricular intensity is a counting statistic, meaning it is sensitive to the amount of time that has passed, and it is a proxy for engagement in time spent in high school, overall. In order to provide a measure of engagement for each school year—as opposed to an overall measure—I use a single component of curricular intensity: highest math course achieved. This is a year-dependent variable. For each year of the transcript, I code a student's value for the highest-level math she achieved to that point in high school. A student in school for four years would have four values, one for each year. I code highest math course where 0 = no math or below algebra I, 1 = algebra I, 2 = geometry, 3 = algebra II, 4 = trigonometry, 5 = pre-calculus, 6 = calculus. This ranking was borrowed from the highest math level ranking available in NCES variables, and adapted for inclusion in curricular intensity (Austin, 2020).

The limitation of using highest math level as a proxy for engagement is that it is a relative measure within one's school or district. Math courses that may represent an advanced level of math for a 9th grader at one school may represent a level that is average or behind for 9th graders in other schools. However, I am unable to center the variable of highest math within each school because of the limited sample from each school. As a result, I address this limitation by coarsening the coding of a student's highest math level into a binary variable indicating whether she was at a higher level of math than the average math level of my sample. The average level of math in my sample was algebra I in 9th grade, geometry in 10th grade, algebra II in 11th grade, and trigonometry in 12th grade. Using this system, a student enrolled in geometry in the 9th grade would be coded as being above average in their math level during their 9th grade year.

I also include a measure of socioeconomic status (SES), which is comprised of parents' education, income, and prestige of parental occupations. I include SES instead of income only because it is a stronger predictor of dropout.

A student's highest math course not only indicates engagement but also may capture variation associated with prior achievement, academic ability, or work ethic. To better account for these characteristics in the highest math variable, I include student scores on an algebraic assessment given at the outset of 9th grade, as well as cumulative grade point average (GPA). I used cumulative GPA instead of prior term GPA because dropping out is a process that is informed by the accumulation of experiences. I also adjust my estimates for student race, sex, age.

After including these adjustments, the interpretation of curricular intensity should be understood as a combination of student engagement and structural opportunity. The measures represent student engagement after adjusting for everything else because higher curricular intensity indicates that students signed up for additional courses or sought more rigorous courses—a possible sign that she was engaged in school to an extra extent. The measure includes structural opportunity because differences in curricular intensity and math level may reflect the differences in courses offered by schools, differences in graduation requirements, or differences in cultural academic expectations. The differences in structural opportunity that curricular intensity and math level measure are likely reduced by adjustments for SES and race—variables that are highly correlated with structural equity, but unlikely to be explained entirely because of unmeasured factors such as neighborhoods.

The measure of a student's highest math course may offer an additional advantage over curricular intensity in separating student engagement from structural opportunity because it is a time-varying variable. This is an advantage because personal engagement levels are more likely to vary over short intervals than the structural elements of a school that impact curricular opportunity. This means that when a student moves from average levels of math to above average levels of math, or vice versa, it is more likely due to a change in their personal engagement levels than a change in school culture or course availability. The clearest way that structural opportunity can vary over time is by transferring to a new school. However, for reasons explained below, students are right-censored, meaning they exit the analytic sample when they transfer to a new school. As a result of students' inclusion in the sample during their time at a single school, the variation in the variable for a student's highest math is more likely to represent changes in engagement than changes in structural opportunity. Changes in a student's highest math level could also be due to other personal characteristics, but after including adjustments for many of those characteristics as outlined above, the remaining predominant factor in credit accrual and mathematic advancement is engagement. I therefore interpret changes in a student's math level as an indicator of their fluctuating engagement.

Dependent measure. The dependent variable of dropout is provided by NCES and indicates if there are any known dropout episodes for each student. Students who returned to school after having dropped out are still recorded as having dropped out at least once and are kept in the dependent measure as a dropout. As a limitation, this measure captures the students for whom a dropout was known. A "no" on this measure does not mean that the student never dropped out, but that no dropout period was ever recorded for the student.

I use three measures of dropout. The first is the variable provided by NCES that indicates whether any dropout episode is known to have occurred. The second and third measures both attempt to identity the time that the dropout incident occurred. Schools did not report the time of any known dropout period, so I calculate it from observed absences in the transcript, and also from self-reported dates of dropout. I calculate it two ways because both only yield dropout dates for approximately 50% - 60% of dropouts, and correlation between the two methods is low, indicating that one cannot be reliably used to "backfill" the other.

Missingness in student reported dropout dates is due to survey nonresponse, but missingness in transcript dropout dates is due to transcripts that show no evidence of a period without enrollment. For the transcript-based measure of dropout time, I coded dropout events as occurring during the first term in which the transcript did not show the student enrolled, excluding summer school. Students with a missing dropout date, per the transcript-calculated dates, are the result of transcripts that never showed an absence of enrollment. The continued enrollment in courses may represent multiple scenarios: students who drop out and return within the same term (e.g., two months later in the same semester); students who drop out, but whose counselors enroll them in courses for the subsequent semesters. This behavior by counselors could be to provide students with a schedule to pick up if they come back, a lack of knowledge that the student was dropping out, or because school funding is based in many states on enrollment numbers.

Descriptive profiles of each sample are reported in Table 3.1 for time-invariant variables and Table 3.2 for time-varying variables.

Table 3.1

Mean Values of Time-Invariant Variables Across Samples

	Transcript-determined	Self-reported	Ever dropped out
Background			
Age at Sep 1, 2009	14.63	14.63	14.65
Female	.50	.50	0.50
Socioeconomic Status	-0.05	-.06	-0.11
Math Score	0.05	.04	-0.03
Race			
White	0.55	0.55	0.52
Black	0.11	0.12	0.13
Hispanic	0.21	0.21	0.23
Asian	0.04	0.04	0.04
Other	0.09	0.09	.09
Percent Dropout	0.02	0.02	.00
Curricular Intensity			5.03
N	9,820	10,030	12,110

Note. Weights used for nationally representative sample.

Table 3.2

Mean Values of Time-Varying Variables Across Time and Samples

Sample	Mean across all years	Year 1	Year 2	Year 3	Year 4
		Mean CTE progress by Year			
Transcript dropout		0.83	1.12	1.50	1.81
Survey dropout		0.83	1.18	1.50	1.80
Ever dropped out	1.15				
		Highest Math Taken			
Transcript dropout		1.26	2.22	3.23	3.96
Survey dropout		1.25	2.22	3.23	3.95
Ever dropped out	2.45				
		Above Average Math Taken			
Transcript dropout		0.31	0.34	0.37	0.40
Survey dropout		0.30	0.34	0.36	0.39
Ever dropped out	N/A				
		Cumulative GPA			
Transcript dropout		2.69	2.69	2.73	2.81
Survey dropout		2.67	2.68	2.73	2.80
Ever dropped out	2.70				
		Sample Size			
Transcript dropout		9,820	9,250	8,530	8,030
Survey dropout		10,030	9,370	8,640	8,110
Ever dropped out	12,110				

Note. Weights used for nationally representative sample.

Missing Data

Although transcript information is complete for those in the sample, only 82% of students with a value for the outcome variable have complete information for all other variables. I address this missing data with a method of multiple imputation, which has been shown to reduce bias more than listwise deletion or other statistical techniques for handling missingness (Allison, 2002). I include cases that have a missing dependent variable in my imputation model to preserve the relationship between all variables in the model (Enders, 2010), and then delete those cases without observed dependent variables (Von Hippel, 2007). I further preserve the structure of the sample by including sampling frame variables (Reiter, Raghunathan, & Kinney, 2006). I create 20 datasets because I have 18% of my sample that is missing at least one variable (Bodner, 2008). All estimations are computed on each of the 20 datasets and then averaged together using pooled standard errors (Rubin, 1988; White, Royston, & Wood, 2011).

Analytic Approach

In order to allow for differing levels of engagement throughout high school I use a discrete time hazards model. This method estimates the probability for dropping out of high school, conditional on not having dropped out of high school in any prior year. It allows for time-varying characteristics, such as changing levels of engagement. This method is preferred to a standard logistic regression model predicting dropout, which cannot include the time-varying predictors that are relevant to this inquiry. The discrete time model also allows students who transfer to be included in the model until they transfer. After transferring they are excluded from the model in subsequent years because of my inability to determine if the student's CTE program from the first school is offered at the new school.

Approximately 11% of students have transcripts with at least one course for which a school year is recorded but no term is recorded. To maximize the sample size, I use school years as the unit of discrete time to allow for their inclusion. The discrete time hazards model is specified as follows:

$$\text{logit } h\left(dropout_{ij}\right) = [\propto_1 D_1 + \propto_2 D_2 + \propto_3 D_3 + \propto_4 D_4] + \beta_1 CTE_{ij} + \beta_2 CumulativeGPA_{ij} + \beta_3 SES_i + \beta_4 \boldsymbol{X}_i \qquad (1)$$

where h is the hazard of dropping out for individual i at time j. The effect of time is modeled in the different constants, given in $\alpha_1 \ldots \alpha_4$. Dummy variables for each time point j are represented in $D_1 \ldots D_4$. Because discrete time hazards models must be interpreted for each year, conditional on no prior occurrence of the target event (dropout), only one dummy variable for each year will be included at any point in the interpretation, and all others disappear. The value for β_1 remains constant for all time periods j because this model assumes that the association between progress in a CTE program and risk of dropping out is constant across all time periods. All time-invariant characteristics other than SES are represented in the vector $\boldsymbol{X}$.

After estimating model one, I proceed to introduce a dummy for whether the student was in a math course level that was above average. Because this variable is a proxy for engagement, and because CTE is theorized to impact dropout through engagement, I expect that the coefficient for CTE will decrease in magnitude in model two. The second model is specified as follows.

$$\text{logit } h\left(dropout_{ij}\right) = [\propto_1 D_1 + \propto_2 D_2 + \propto_3 D_3 + \propto_4 D_4] + \beta_1 CTE_{ij} + \beta_2 AboveAvgMath_{ij} + \beta_3 CumulativeGPA_{ij} + \beta_4 SES_i + \beta_5 \boldsymbol{X}_i \qquad (2)$$

I next estimate the same model but with an interaction between the time varying CTE progress variable and the dummy for whether a student is taking math courses at an above average level or not. Under the hypothesis that CTE benefits disengaged students, I expect that the students who are above average in math would have part of the benefit from CTE canceled out by an opposite signed coefficient on the interaction. Adding the interaction changes the equation in the following way:

$$\text{logit } h\left(dropout_{ij}\right) = [\propto_1 D_1 + \propto_2 D_2 + \propto_3 D_3 + \propto_4 D_4] + \beta_1 CTE_{ij} + \beta_2 AboveAvgMath_{ij} + \beta_3 CTE_{ij} * AboveAvgMath_{ij} + \beta_4 CumulativeGPA_{ij} + \beta_5 SES_i + \beta_6 \boldsymbol{X}_i \quad (3)$$

I next make changes to the model to address recent suggestions that the association between CTE and dropout varies by year, such that the protective association of CTE against dropout increases when taken in later years of high school (Gottfried & Plasman, 2018). This violates the proportionality assumption inherent to discrete time hazards modeling, which is that all predictors are assumed to have an identical effect at all time points (Singer, Willet, & Willet, 2003). Accommodating its violation requires the following changes to the model:

$$\text{logit } h\left(dropout_{ij}\right) = [\propto_1 D_1 + \propto_2 D_2 + \propto_3 D_3 + \propto_4 D_4] + [\beta_1 CTE_i D_1 + \beta_2 CTE_i D_2 + \beta_3 CTE_i D_3 + \beta_4 CTE_i D_4] + \beta_5 AboveAvgMath_{ij} + [\beta_6 CTE_i * AboveAvgMath_{ij} D_1 + \beta_7 CTE_i * AboveAvgMath_{ij} D_2 + \beta_8 CTE_i * AboveAvgMath_{ij} D_3 + \beta_9 CTE_i * AboveAvgMath_{ij} D_4] + \beta_{10} CumulativeGPA_{ij} + \beta_{11} SES_i + \beta_{12} \boldsymbol{X}_i \quad (4)$$

where the dummy variables for each year $D_1 \ldots D_4$ are multiplied by the effect of CTE progress to create a distinct effect of CTE in each year. The respective coefficients $\beta_1 \ldots \beta_4$ should not be interpreted individually as compared to the other three; instead they should be interpreted as the effect of CTE on dropout in that given year, conditional on not having dropped out or transferred prior to that time. The same parameters for interpretation also apply to the interaction between CTE and above average math.

I estimate these same models for both of the different dropout times—the transcript-dropout and the survey-dropout. Due to the large proportion of dropout date missingness among dropouts for both datasets, I also estimate the association between CTE participation and dropout using summary measures, post-hoc. This method does not provide the advantages of the discrete time hazards analysis and requires all variables to be treated as time invariant. However, it includes all students known to have experienced a dropout episode and may help triangulate the results with the other datasets. To estimate it, I use a logistic regression as follows:

$$\log\left(\frac{p_i(dropout)}{1-p_i(dropout)}\right) = \beta_0 + \beta_1 CTE_i + \beta_2 \boldsymbol{X}_i \qquad (5)$$

Where p is the probability of dropping out of high school, i is the individual student, $\boldsymbol{X}$ is a vector of GPA and student characteristics measured in the fall of 9th grade in order to represent students at the outset of high school. Subsequently, I re-estimate the same model with the addition of curricular intensity as well as variants that coarsen curricular intensity into a binary variable indicating whether a student has above average curricular intensity. After adding an interaction between being above average in curricular intensity and participation in CTE, my model is estimated as follows:

$$\log\left(\frac{p_i(dropout)}{1-p_i(dropout)}\right)$$

$$= \beta_0 + \beta_1 CTE_i + \beta_1 AboveAvgCI_i + \beta_1 AboveAvgCI_i * CTE_i + \beta_2 \boldsymbol{X}_i \qquad (6)$$

The results of the estimations are provided in log odds for all models to allow for the clearest representation of statistical significance. For ease of interpretability, predicted probabilities are also provided in graphs and a table.

Results

The analysis of all three datasets indicated that participation in CTE is associated with decreased odds of dropping out. The two datasets that allow for discrete time hazard modeling indicate that the effect of CTE varies over time, although a pattern is not clear in the fourth model for each dataset. In the transcript-derived dropout date dataset CTE seems to be most protective in the first year. In the survey-derived dropout date dataset it appears most protective in the fourth year.

In the transcript dropout dataset, seen in Table 3.3, participation in CTE in the first year of high school brings the greatest reduction in the odds of dropping out. However, in the same dataset, participation in CTE is associated with decreased dropout odds in all four years.

Figure 3.1 shows that the difference between no CTE participation and having accumulated four CTE courses is associated with a decrease in the probability of dropping out of at least five-fold—a finding that is consistent across all years for students in average or below average math courses. The benefit for students in above average math courses is more subtle. The only group that does not benefit are first-year high school students in above average math classes. However, first-year high school students who are in above average math classes do not have a high baseline probability of dropping out, regardless of CTE. This is true even if other characteristics, such as SES or GPA are below average. Students one standard deviation below the mean on SES and GPA have a less than 1% probability of dropping out if enrolled in above average math classes. CTE participation for this population is still associated with a decreased probability of dropping out.

Table 3.3

Discrete Time Hazards Model of Dropout, as Time of Dropout is Determined by Transcript

	1	2	3	4
Background				
Age	0.66***	0.65***	0.65***	0.64***
	(0.14)	(0.14)	(0.14)	(0.14)
Female	0.25	0.24	0.24	0.24
	(0.13)	(0.13)	(0.13)	(0.13)
Socioeconomic Status	-0.35*	-0.34*	-0.34*	-0.34*
	(0.14)	(0.14)	(0.14)	(0.14)
Math Score	0.02	0.08	0.08	0.08
	(0.08)	(0.09)	(0.09)	(0.09)
Race				
Black	-0.22	0.22	0.22	-0.19
	(0.16)	(0.22)	(0.22)	(0.16)
Asian	0.20	-0.43	-0.43	0.22
	(0.23)	(0.37)	(0.37)	(0.23)
Hispanic	-0.54	-0.19	-0.19	-0.42
	(0.36)	(0.16)	(0.16)	(0.36)
Other	-0.36	-0.36	-0.36	-0.36
	(0.21)	(0.21)	(0.21)	(0.21)
Schooling				
Cumulative GPA	-1.91***	-1.83***	-1.83***	-1.83***
	(0.07)	(0.10)	(0.10)	(0.10)
CTE Progress	-0.49***	-0.51***	-0.53***	
	(0.07)	(0.07)	(0.07)	
CTE Progress * Year 1				-0.82*
				(0.36)
CTE Progress * Year 2				-0.53**
				(0.17)
CTE Progress * Year 3				-0.43**
				(0.13)
CTE Progress * Year 4				-0.58***
				(0.11)
Above Average Math Course Level		-1.07***	-1.47***	-1.44***
		(0.25)	(0.25)	(0.34)
Above Average Math * CTE Progress			0.34	
			(0.20)	
CTE Progress * Year 1 * Above Average Math Level				0.97
				(0.69)
CTE Progress * Year 2 * Above Average Math Level				-0.03
				(0.41)
CTE Progress * Year 3 * Above Average Math Level				0.26
				(0.22)
CTE Progress * Year 4 * Above Average Math Level				0.41
				(0.10)
Time				
Year 1	-1.00*	-1.01*	-1.02*	-1.01*
	(0.45)	(0.44)	(0.44)	(0.51)
Year 2	0.07	-0.06	-0.06	-0.00
	(0.39)	(0.38)	(0.38)	(0.46)
Year 3	0.25	0.26	0.26	0.09
	(0.22)	(0.22)	(0.22)	(0.30)
Year 4 (Constant)	-0.73	-0.68	-0.65	-0.59
	(0.58)	(0.57)	(0.57)	(0.59)
N	9,820	9,820	9,820	9,820

Table 3.3 (Continued)

Note. GPA centered at the mean GPA for the sample. Weights used.

In contrast with the first dataset, the survey-reported dropout dataset produces results indicating that CTE participation in the first two years of high school is not significantly associated with decreased odds of dropping out. As seen in Table 3.4, the third and fourth years of high school are significantly associated with decreased odds of dropping out. The magnitude of lowered odds of dropout increases the longer that students have been in school. Although the decreased probability of dropping out is observed for all students in average or below average math classes, it is most pronounced for students with the GPA and SES level of the average dropout in my sample. For students of all backgrounds, participation in CTE during the first year of high school is associated with increased probability of dropping out, although this is statistically insignificant.

A trend that may be related to some of the observed outcomes is the probability of dropping out by year in high school. Both datasets include models that estimate the odds of dropping out at the beginning of high school to be lower than at the end of high school; the risk of dropout is higher in the third and four year than in the first or second. This may be due to changing laws that have raised the minimum age that must be reached before dropping out.

Table 3.4

Discrete Time Hazards Model of Dropout, as Time of Dropout is Self-Reported by Survey

	1	2	3	4
Background				
Age	0.61***	0.60***	0.60***	0.61***
	(0.12)	(0.12)	(0.12)	(0.12)
Female	0.22	0.22	0.21	0.21
	(0.12)	(0.12)	(0.12)	(0.12)
Socioeconomic Status	-0.34**	-0.32*	-0.32*	-0.33*
	(0.12)	(0.12)	(0.12)	(0.12)
Math Score	0.03	0.08	0.08	0.07
	(0.08)	(0.08)	(0.08)	(0.08)

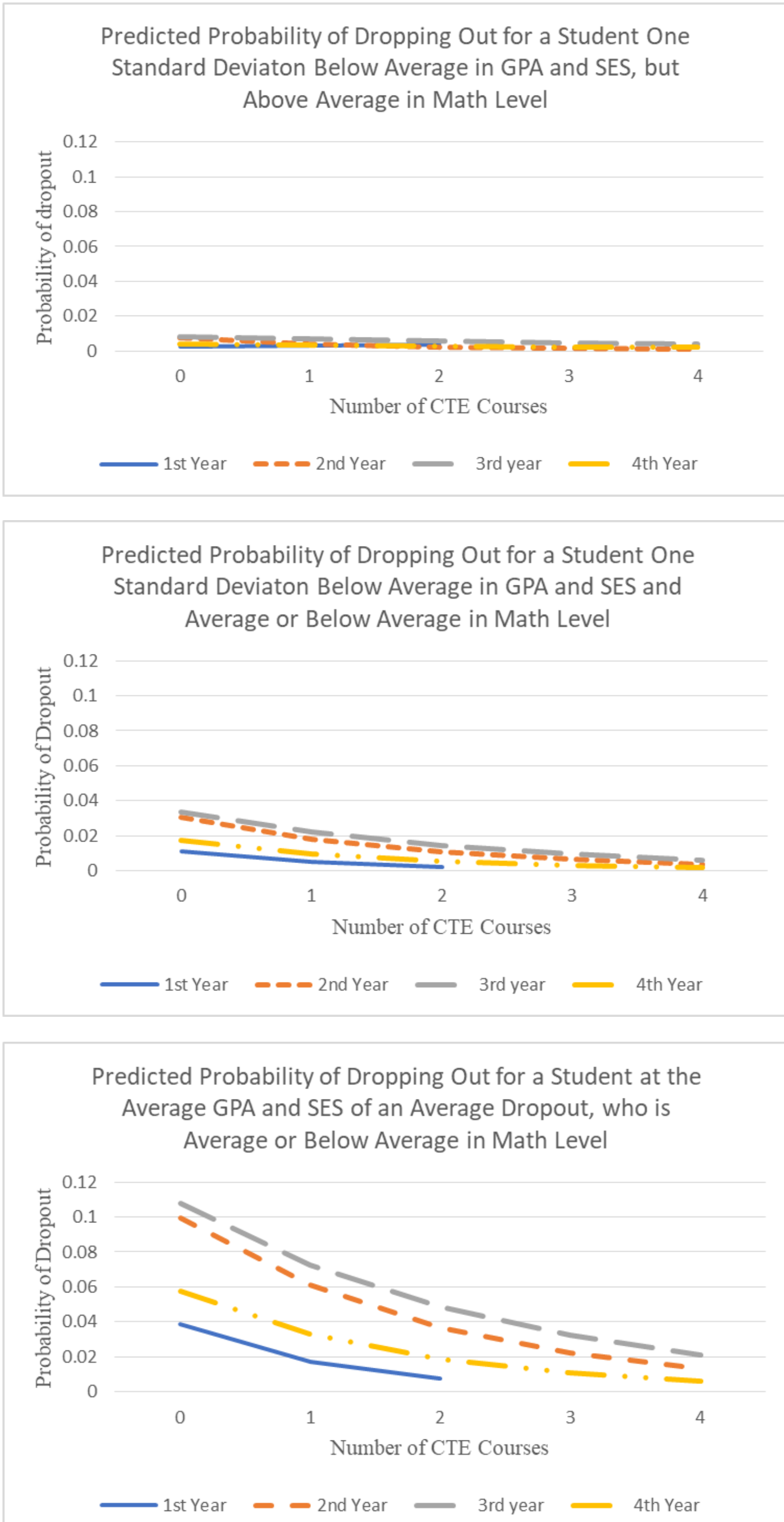
Table 3.4 (Continued)

Race				
Black	-0.35	0.11	0.10	-0.33*
	(0.15)	(0.20)	(0.19)	(0.15)
Asian	0.09	-0.42	-0.43	0.11
	(0.20)	(0.38)	(0.38)	(0.20)
Hispanic	-0.51	-0.33	-0.33	-0.46
	(0.37)	(0.15)	(0.15)	(0.40)
Other	-0.25	-0.26	-0.26	-0.25
	(0.18)	(0.18)	(0.18)	(0.19)
Schooling				
Cumulative GPA	-1.79***	-	-	-1.76***
	(0.09)	1.73***	1.72***	(0.09)
		(0.09)	(0.09)	
CTE Progress	-0.32***	-	-	
	(0.07)	0.32***	0.37***	
		(0.07)	(0.07)	
CTE Progress * Year 1				0.19
				(0.22)
CTE Progress * Year 2				-0.17
				(0.18)
CTE Progress * Year 3				-0.31*
				(0.13)
CTE Progress * Year 4				-0.67***
				(0.10)
Highest Math Course Taken				
Above Average Math Course Level		-	-	-1.42***
		0.75***	1.39***	(0.25)
		(0.19)	(0.07)	
Above Average Math * CTE Progress			0.47***	
			(0.13)	
CTE Progress * Year 1 * Above Average Math Level				-0.02 (0.44)
CTE Progress * Year 2 * Above Average Math Level				0.70** (0.24)
CTE Progress * Year 3 * Above Average Math Level				0.20 (0.25)
CTE Progress * Year 4 * Above Average Math Level				0.69*** (0.17)
Time				
Year 1	-0.45	-0.44	-0.46	-1.16**
	(0.41)	(0.40)	(0.40)	(0.44)
Year 2	-0.24	-0.24	-0.25	-0.83*
	(0.30)	(0.30)	(0.30)	(0.39)
Year 3	-0.08	-0.07	-0.07	-0.50
	(0.21)	(0.21)	(0.21)	(0.32)
Year 4 (Constant)	-0.65	-0.63	-0.59	-0.16
	(0.46)	(0.45)	(0.45)	(0.47)
N	10,030	10,030	10,030	10,030

Note. GPA centered at the mean GPA for the sample. Weights used.

Figure 3.1

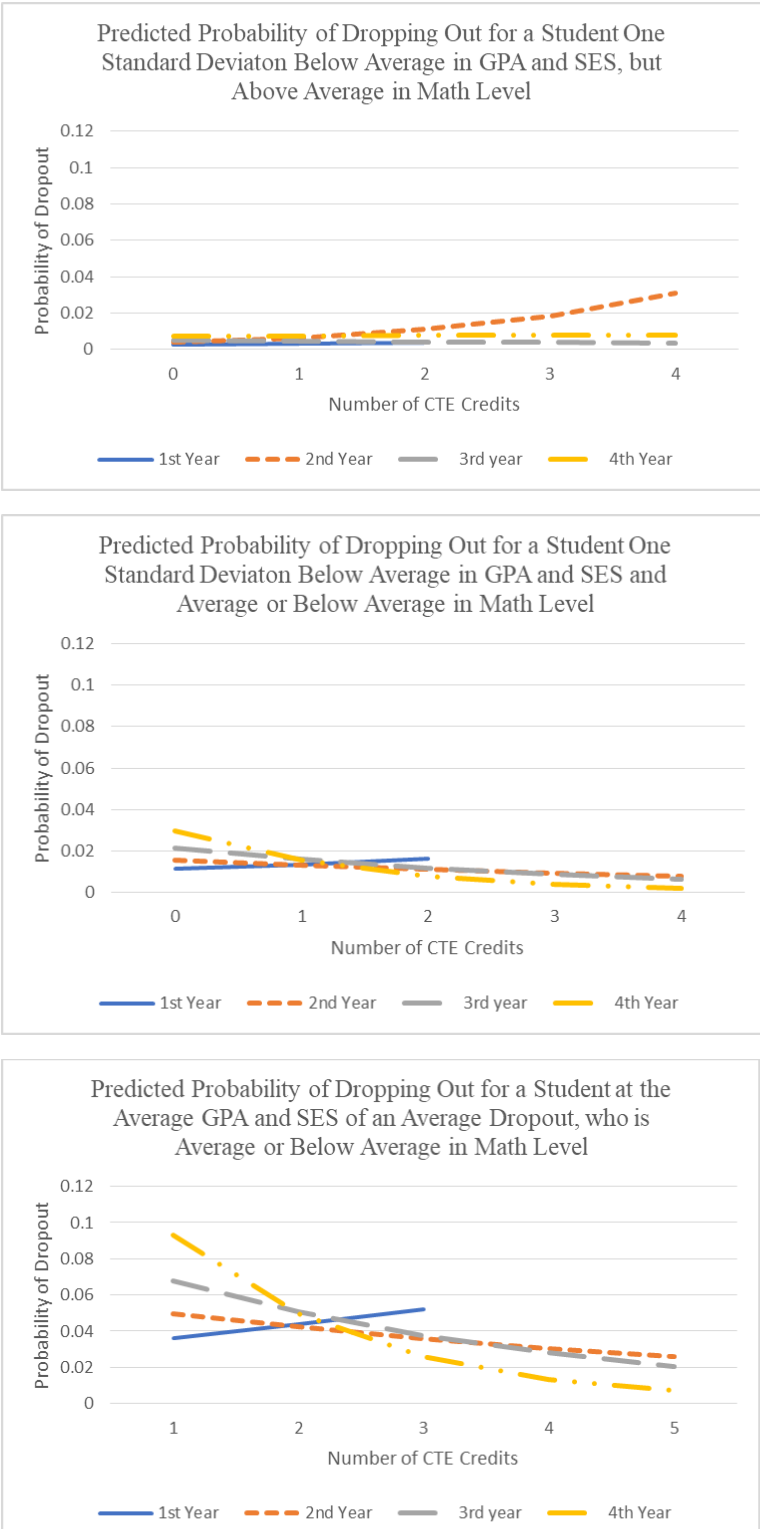
Predicted Probabilities for CTE Participants from Transcript Dropout Dates



Note. The sample did not have enough observations with more than 2 CTE credits in the 1st year.

Figure 3.2

Predicted Probabilities for CTE Participants from Survey Dropout Dates



Note. The sample did not have enough observations with more than 2 CTE credits in the 1st year.

Table 3.5 shows results from the final dataset, which reveals a similar pattern of decreased dropout for CTE participants. Each CTE course taken in a program of study is associated with lower odds of dropping out. This association remains significant even after introducing a measure for the advanced level of student coursework. For students with an above average level of academic curricular intensity, CTE remained associated with decreased likelihood of drop-out. The interaction between CTE participation and having an above average level of curricular intensity was non-significant. This indicates the association between CTE and dropout is consistent for all students. However, the probability of dropping out is higher for those with low curricular intensity than those with high levels of curricular intensity.

The predicted probabilities in Table 3.6 allow for an easier interpretation of changes in dropout probability associated with CTE participation than provided by the log odds analyses. The table considers students who participate in three CTE courses in a program of study. Without adjusting for curricular intensity, the table shows results that are consistent with prior findings on dropout: participation in CTE is associated with substantive decreases in dropout probability for all students, but the benefit is more pronounced for students with below average SES and math scores. The increased benefit of CTE participation for students of lower SES can be seen by comparing dropout probabilities. The probability of a student who is one standard deviation above the mean in SES and in their math test scores dropping out is reduced from 8% to 4% if they participate in CTE. If the same student were one standard deviation below the mean in the same area, the probability of dropping out would reduce from 12% to 6% upon participating in CTE. In other words, when modeling the relationship between CTE and dropout, the reduction in dropout probability is largest for low SES and low math students.

Table 3.5

Log Odds of Relationship Between Dropout and CTE Involvement

	1	2	3	4
Background				
Age	0.64***	0.56***	0.63***	0.62***
	(0.10)	(0.09)	(0.09)	(0.09)
Female	0.18	0.23*	0.19	0.19
	(0.11)	(0.10)	(0.11)	(0.10)
Socioeconomic Status	-0.29**	-0.20*	-0.25**	-0.25**
	(0.09)	(0.09)	(0.09)	(0.09)
Math Score	-0.05	0.13	0.05	0.05
	(0.07)	(0.07)	(0.07)	(0.07)
Race				
Black	-0.07	0.19	0.05	0.04
	(0.16)	(0.16)	(0.17)	(0.17)
Asian	0.15	0.45*	0.31	0.31
	(0.22)	(0.23)	(0.22)	(0.22)
Hispanic	-0.33*	-0.16	-0.23	-0.24
	(0.14)	(0.15)	(0.15)	(0.15)
Other	-0.23	-0.16	-0.21	-0.20
	(0.22)	(0.22)	(0.22)	(0.22)
Schooling				
Cumulative GPA	-1.53***	-1.10***	-1.35***	-1.34***
	(0.09)	(0.10)	(0.09)	(0.09)
CTE Progress	-0.27***	-0.22***	-0.28***	-0.31***
	(0.05)	(0.05)	(0.06)	(0.07)
Curricular Intensity		-0.37***		
		(0.03)		
Above Average Curricular Intensity			-0.87***	-1.16***
			(0.13)	(0.22)
CTE Progress * Above Avg. Curricular Intensity				0.18
				(0.11)
Constant	1.81***	2.22***	1.66***	1.71***
	(0.22)	(0.25)	(0.22)	(0.22)
N	9,330	9,330	9,330	9,330

Note. GPA centered at the mean GPA for the sample. Weights used.

The estimates change when adjusting for curricular intensity. Among students at the mean level of curricular intensity, the change in the probability that accompanies CTE concentration is nearly uniform and minimal for all groups—a reduction in the probability of dropping out from 7-8% without CTE to 3-4% with CTE. This indicates that at an average level of curricular intensity, students of low SES backgrounds are similar in their probability of dropping out as their high SES peers.

For students who are one standard deviation below the mean level of curricular intensity, concentration in CTE is associated with the greatest reduction in the probability of dropping out. For high SES students with low curricular intensity the probability of dropping out is reduced from 15% to 8% after CTE participation; for low SES students with low curricular intensity the probability of dropping out is reduced from 17% to 9%.

Table 3.6

Predicted Probability (PP) of White Male students in Public High Schools Dropping Out, by Socioeconomic Status, Math Score, and Curricular Intensity

	Without adjusting for curricular intensity			Adjusting for average curricular intensity			Adjusting for 1 SD below average curricular intensity		
	CTE	No CTE	Change in PP	CTE	No CTE	Change in PP	CTE	No CTE	Change in PP
1 SD above in SES & Algebraic Assessment	.03	.08	.04	.04	.07	.03	.08	.15	.07
Average SES & Algebraic Assessment	.04	.10	.05	.04	.07	.04	.08	.16	.08
1 SD Below in SES & Algebraic Assessment	.06	.12	.07	.04	.08	.04	.09	.17	.08

Note. The amount of CTE taken in these probabilities is 3 courses.

Comparing results of analyses focused on the model without curricular intensity to the model with curricular intensity, there is one general finding: participation in CTE reduces the probability of dropping out of school by approximately half. The inclusion of curricular intensity indicates that the group most at risk is not purely low SES students. Rather, the group with the highest risk for dropout is the group with low levels of curricular intensity.

Discussion

My findings support others' reports that CTE is associated with a decrease in dropout probability for students from low-SES families more than from high-SES families (Dougherty, 2018). However, my results deviate from other work in that I find that SES is not the strongest predictor of which students decrease the probability of dropping out. I find that a student's level of engagement in their coursework is a better indicator of which students experience the benefit of dropout reduction.

This is an important finding because most prior studies for the past two decades have focused on students' background characteristics such as SES to explain the benefits of CTE or vocational education (Plank, 2001; Dougherty, 2018). I found that, after controlling for curricular intensity and its representation of engagement, there is little benefit to focusing on students' SES. The students most likely to boost their graduation chances by taking CTE courses are those with low engagement. This has likely been clouded before because low engagement is correlated with low SES. For those asking the persistent question, "For whom does CTE work best?" the answer is clear: it works best at reducing dropout for students who are disengaged, regardless of background.

Given these results, a challenge for education stakeholders is to decide how to appropriately leverage the advantages associated with CTE on behalf of students who could benefit most. Policies encouraging increased participation in CTE for disengaged students or students with low levels of curricular intensity may be problematic. CTE is a descendent of vocational education, which carried a long history of tracking the lowest performers towards a differential post-secondary destination (e.g., work rather than college). How should counselors navigate CTE participation in light of these findings?

This challenge can be dismissed by keeping the perspective that CTE's primary goal is not to engage students or to prevent them from dropping out. The main focus of CTE is to prepare students with technical skills that lead to improved preparation for post-secondary education and for the workforce—a focus that could be useful to all students. Counselors can advertise and enroll all students in CTE, even though this secondary benefit only helps those most at risk.

My results also allow for insights into recent work about the timing of CTE course-taking, because it models CTE's effect as distinct in each time period. When I constructed my dropout data by survey date, as Gottfried and Plasman (2018) did, I found the same phenomenon they did: CTE taken at the end of high school is associated with higher levels of protection against dropout than CTE taken early in high school. In contrast to their reported results, which omit reporting the base probability of dropping out for all students in each year, I find that all students experience an increased base probability of dropping out as they spent more time in school and got older. The relationship between number of years in school and base probability for dropping out may be explained by recent changes to law that increased the legal age for dropout to 18, thus making it more difficult for students to drop out before the final years of high school. As such, the pronounced benefit of CTE at the end of high school may be observed because there is a greater ability for students to legally dropout.

Under the assumption that the baseline probability for dropping out increases as a student approaches the legally-allowed age for doing so, then my models and others' (Gottfried & Plasman, 2018) performed as expected. The risk of dropping out was reduced for CTE participants in greatest measure as they approach age 18. This means that the mechanism of reengaging students in school through CTE may be active for students throughout their high school years.

If CTE reengages students in every year of high school, then it should have shown as a significant interaction between CTE participation and student math level. This was not the case; students with lower engagement did not benefit more from CTE than their peers in every year. Instead, they benefitted more in the second and fourth years. This pattern is unusual—why not the third year also? It may be that as students approach the age when dropping out is allowed, all students, even those in high-level courses, begin to experience flagging levels of engagement. If true, participation in CTE would benefit all students because all students would be experiencing some level of disengagement. Under this circumstance, the interaction between CTE participation and highest level of math would be insignificant, but the main effect of CTE would be significant. This is what I observed. However, future research will be needed to clarify this curious result.

In sum, the results of this study shed light both on the mechanism through which CTE is associated with dropout as well as the group that is most likely to benefit from CTE. It does so by providing empirical support for the belief that CTE increases student engagement in school, and suggests that those with low engagement may benefit most from CTE. This finding is helpful for schools that may be considering increasing their CTE programs to combat high dropout rates. CTE is listed by the National Dropout Prevention Society as a recommended practice for reducing dropout (Grams, 2014). By offering robust and healthy CTE programs, schools offer disengaged students a productive curricular outlet that is likely to benefit both student and school with increased graduation rates.

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Chapter IV

The Role of Career and Technical Education

in College Enrollment

Introduction

College enrollment is an implicit goal of the current design of career and technical education (CTE). This goal is due to three changes that made over the past thirty years. First, changes to several U.S. industrial sectors increased the need for workers with at least a two-year degree (Carnevale, Smith, & Strohl, 2010). Second, the level of educational competition increased among workers themselves (Carnevale, Strohl, Cheah & Ridley, 2017). Third, changes were introduced into the federal design of CTE that now encourage the alignment of secondary school CTE courses with two-year post-secondary credentials (Gordon, 2014). The first and second changes to the labor force occurred gradually, over time. The third change to the federal design of CTE occurred swiftly in 2006 when a funding bill, known as Perkins IV, was passed (Threeton, 2007). So far, no one has evaluated the relationship between CTE participation and college enrollment after the 2006 design change.

Despite the dearth of research on the impact of secondary CTE on college enrollment after 2006, there has been interest in understanding the relationship. Others have evaluated the relationship using data from the 1980s, 1990s, and early 2000s (Arum & Shavit, 1995; DeLuca, Plank, & Estacion, 2006; Gottfried & Plasman, 2018; Kriesman & Stange, 2017). These efforts produced a body of literature that shows changes over time in the college enrollment rates of high school CTE participants. Several decades ago, in the 1980s, the probability of a student attending college after participating in CTE was low (Arum & Shavit, 1995). One decade later, in the 1990s, CTE was still associated with a low probability of enrolling in college, but not to the same magnitude as in the prior decade (DeLuca et al., 2006; Kriesman & Stange, 2017). One decade later, in the early 2000s before Perkins IV, participation in CTE no longer predicted college enrollment; students were just as likely to enroll in college after participating in CTE as were non-CTE participants (Gottfried & Plasman, 2018).

By looking across the studies, it appears that changes to CTE over time produced an increased level of students' college enrollment. However, this is an unsupported conclusion to draw from this evidence because it presumes that while CTE changed to provide more support, the rate of college enrollment remained stable over time. In fact, college enrollment rates did not remain stable over time, but rose annually during the 1980s, 1990s, and 2000s (Statistica, 2018). During these decades, educators emphasized that all children should be prepared for and attend college (Rosenbuam, Miller, & Krei, 1996). To enable more (or all) children to attend college, the level of academic preparation in schools increased. The average number of earned academic credits increased (Hudson, 2013), curricular standards for academic subjects were introduced and refined (Smith, 2004), and legislation such as *No Child Left Behind* was passed.

The increases to students' level of academic preparation correlate with the timing of the increased emphasis on preparation for and enrollment in college. Estimates of CTE's relationship with college enrollment would be improved by including adjustments for students' academic preparation. A recent refinement (Austin, 2020) to an established instrument (Adelman, 1999; 2006) known as curricular intensity, allows for the measurement of students' academic preparation throughout high school. By measuring and adjusting for students' curricular intensity, I reduce the confounding effect of non-CTE pressures on college enrollment. This allows me to produce cleaner estimates of the relationship between CTE and college enrollment. I do this using a dataset of students who enrolled in high school after Perkins IV was implemented.

Literature Review

College enrollment is an implicit goal of the current design of career and technical education (CTE). I will discuss three reasons why college may be viewed as an implicit goal for college: the federal design of CTE, changes to U.S. industrial sectors that increase the need for college-trained workers, and the increasing level of educational competition among workers, themselves.

Attending college can be inferred as a goal of CTE from language in the federal bill that funds it, *The Carl D. Perkins Career and Technical Education Act of 2006*—widely known as Perkins IV. This law determined that CTE content should be "aligned with challenging academic standards and relevant technical knowledge and skills needed to prepare for further education and careers in current or emerging professions" (*Carl D. Perkins Career and Technical Education Act of 2006*; Dortch, 2012, p. 4).

This language is noteworthy because of its contrast with prior funding bills. Perkins IV was the first to include alignment with academic standards in its design for its courses. By changing the design of CTE to align its content with challenging academic standards, lawmakers signaled a shift in the goals of CTE towards those of the academic classroom (Threeton, 2007), where college readiness is arguably paramount (Conley, 2007; Roderick, Nagaoka, Coca, 2009). The same signaling towards college readiness is seen in language that is *not* included in Perkins IV. Specifically, language from Perkins III that limited CTE's scope to preparation for careers "other than [those] requiring a baccalaureate, master's, or doctoral degree" (*Carl D. Perkins Vocational and Applied Technology Education Act of 1998*, p. 112) was removed in Perkins IV.

College may also be viewed as an implicit goal of CTE due to changes in the workplace. Because a primary objective of CTE and its predecessor, vocational education, has always been to prepare students for the workforce, it inherently carries the objective of delivering to students the education and training required for entry and success in the workforce. Such education and training increasingly mean college (Carnevale et al., 2017) because of three trends. The industries experiencing the most growth are those which require post-secondary education (Deutsch, 2019). Industries that have traditionally relied on manual-labor are becoming more tech-heavy (Eckelkamp, 2018). Blue-collar jobs are disappearing (Baker & Buffie, 2017).

The changes in the workplace have largely come as the supply of college-educated workers in the workforce has increased. The increase in the supply of college-educated workers to the labor market is the third reason CTE may be seen to have an implicit goal of college enrollment. The educational bar to be competitive with others on the job market is rising. In 1991, 60% of the workforce with good jobs had less than a bachelor's degree and 32% of all workers' highest level of education was high school or less. In 2015, these proportions decreased to 45% and 20%, respectively (Carnevale et al., 2017). The decrease in workers with only a high school education indicates an increase in the supply of workers with higher levels of education. However, it does not necessarily mean that higher levels of education were required for the job positions that they were hired into. The high bar for educational competitiveness is not limited to jobs for which higher education is actually required. Of all U.S. workers with a bachelor's degree, 38% work in a job that does not require any college degree (Abel & Deitz, 2014).

These labor market trends affect CTE because the goal of CTE is to increase participants' technical skills and training to make them competitive in the labor market. Increasingly, that means college enrollment after high school (Carnevale, Smith, & Strohl, 2010; Hanushek, Schwerdt, Woessmann, & Zhang, 2017). As mentioned earlier, one way that CTE was redesigned to support students was to introduce programs of study that articulate high school offerings with local two-year programs (Passarella, 2018).

One way that Perkins IV changed the design of CTE to align with post-secondary education was to introduce the concept of programs of study. The programs of study that Perkins IV called for amount to deliberate sequencing of courses to provide a cohesive, targeted CTE curriculum (Castellano, Sundell, Overman, & Aliaga, 2012). Programs of study are intended to guide students, so when they finish high school they are primed to enter an aligned two-year post-secondary having already completed some of the entry-level coursework (Dortch, 2012). In order to construct a program of study, the school must not only determine which courses should be taken together or in sequence, but also which courses need to be offered to support targeted industries. When a school has completed the process of designing a program of study, the plans are sent to the state office of education for approval (Dortch, 2012).

Deliberately progressing through CTE in a program of study that has been aligned with local two-year college programs contrasts starkly with the à la carte method of selecting CTE courses prior to Perkins IV. Of course, students still have the flexibility to participate à la carte if they prefer, but programs of study provide clear structure and goals that align with post-secondary education.

The changes to the design of CTE, along with evolutions in United States industries, coalesce to connect CTE implicitly to the goal of college enrollment. They do so because it is, now, more occupationally expedient to enroll in college than ever before. CTE students preparing for today's labor market have a self-interested reason to pursue post-secondary education. explain associated benefits of CTE in reduced high school dropout rates (Dougherty, 2018; DeLuca et al, 2006; Gottfried & Plasman, 2018; Plank, 2001; Plank, DeLuca, & Estacion, 2008).

Educational engagement is defined as having four facets: academic, social, cognitive, and affective. It is strongly tied to educational outcomes of persistence and achievement (Finn & Zimmer, 2012). CTE may increase levels of overall academic engagement as CTE offers students opportunities for increased autonomy, provides a sense of competency, and connects its subject matter more immediately to the real-world (Gentry, Peters, & Mann, 2007). Each of those factors has been associated with students' overall motivation (Pintrich, 2003). Students report that CTE courses are more positive experiences over and above academic classes (Gentry, Peters, & Mann, 2007). This may indicate that CTE makes social engagement—interacting appropriately in classroom behavior and activities—easier.

Affective engagement, or the level of personal emotional response from involvement, may also be affected because participation in CTE is associated with improvements in self-worth (Kelly & Price, 2009). This form of educational engagement may be especially pronounced for students with low academic achievement (Dougherty, 2018), possibly because they have the greatest need to identify with a structured, reliable program or hobby (DeLuca, Clampet-Lunquist, Edin, 2016).

Students who experience a boost in educational engagement through CTE may feel a need to persist in their education and reach for the next rung of success (Finn & Zimmer, 2012). In the current climate, success is often seen as going to college—a mindset that is held by most high-school students (Rosenbaum, 2001), and is the expected outcome for life after high-school of most students (Rosenbaum, Stephan, & Rosenbaum, 2010). Therefore, participation in CTE may lead a student to pursue further education.

It is also possible that the introduction of programs of study may amplify engagement when compared to engagement levels found in CTE students who participate à la carte (Castellano, Ewart Sundell, & Richardson, 2017). The increased engagement would then be channeled, via their program of study, into a course structure that purposefully leads up to post-secondary enrollment.

Efforts to measure the potential effect of CTE participation on post-secondary enrollment, or to evaluate CTE's effectiveness in articulating with two-year programs, are complicated by some of the same factors that led to its 2006 redesign. Those factors were the changes in the labor market as explained above, as well as residual pressures to improve academic preparation in schools, echoing the landmark 1983 report, *A Nation at Risk*. That early report indicated that if another nation had thrust on the United States its current educational system that the U.S. would have seen it as an act of war (National Commission on Excellence in Education, 1983). That report served as something of a turning point in United States education (Bell, 1993), leading to the establishment and refinement of educational academic standards (Smith, 2004). The movement for reform not only included academics but also focused on encouraging all students to prepare for college (Rosenbuam, Miller, & Krei, 1996; Schneider & Stevenson, 1999). This focus is embodied in the name of legislation stemming from that time period: *The No Child Left Behind Act of 2001*. During the early 2000s math, science, and social studies course loads increased (Hudson, 2013) and colleges saw 33% more students enrolling than they did 10 years earlier (Statistia, 2018).

These changes are relevant to research about CTE and college enrollment because they represent non-CTE pressures on college enrollment. Ignoring them could lead to a misattribution of the causes for changing trends in college enrollment.

Indeed, the trends in college going among CTE students have changed. College enrollment rates for vocational students, overall, increased through the 1980s and into the 2000s as CTE emerged (Dalton, Lauff, Henke, Alt, & Li, 2013). Although this is the simple overall trend of raw college enrollment rates among vocational and CTE students, the trend does not change when adjusting for confounding variables of student background, aptitude, and performance (Arum & Shavit, 1995; DeLuca, Plank, & Estacion, 2006; Gamoran & Mare, 1989; Kreisman & Stange, 2017). Just before Perkins IV was passed, students were no more and no less likely to attend college after participation in CTE (Gottfried & Plasman, 2018). That is, for first time in decades, students in CTE were not less likely than non-CTE students to enroll in college. However, students who enrolled in college after participating in CTE were more likely to enroll in a two-year program than their non-CTE, college-enrolled peers (Dougherty, 2016; Gottfried & Plasman, 2018; Kreisman & Stange, 2017). This is possibly explained by the emphasis through programs of study on articulation with two-year college programs. In all of the prior research there was a gap in the knowledge base because no one had adjusted analyses for students' level of academic preparation, which as discussed above, was increasing during the same time period.

A recent refinement (Austin, 2020) on an established measure (Adelman, 1999; 2006) of academic course taking, known as curricular intensity, represents academic preparation levels. Curricular intensity combines both the quantity and quality of an academic schedule across all four core subjects—math, English, science, and social studies—into a single numeric indicator (Adelman, 1999; 2006; Austin, 2020). Although curricular intensity has been widely used (Attewell & Domina, 2008; Long, Conger, & Iatarola, 2012), it was not readily available for use in any dataset except those from the late 20th century (Adelman 1999, 2006)—well before

Perkins IV. This changed with its recent refinement (Austin, 2020), which uses a more parsimonious algorithm while also slightly outperforming the original construction of the measure (Austin, 2020). More information comparing the original to the refined measure of curricular intensity can be found in Chapter II. Austin's refinement (2020) makes it calculable in new datasets, which allows for its use in more current datasets.

The use of curricular intensity may also provide a second benefit in studies of CTE, in addition to accounting for academic preparation. As the course taking compliment to CTE, the measurement of one's academics may serve as a measure of personal interest in CTE. This may seem counterintuitive, but scheduling courses is a balancing act. In order to schedule additional CTE courses, a student must decrease the number of additional academic courses he might have taken instead. Although students could also balance their schedule by changing their participation in foreign language or fine arts classes, adjusting CTE and academic courses appears more likely. This is because CTE and academic courses contribute the most credits to students' high school records. Students take approximately two times more credits in CTE than either foreign languages or fine arts (NCES, 2016).

Using curricular intensity as an adjustment variable provides distinct advantages when estimating the association between CTE and college enrollment. It will also allow for additional insight into the decision for students enrolling in college about whether to enroll for a two-year or four-year degree. These advantages occur because curricular intensity accounts for the changes in academic preparation influenced by contemporary societal pressures. Its rich variation allows for more informed and better fitting statistical models. Lastly, it is well suited to questions of a national and generalizable nature.

Method

Data and Sample

It is imperative to use data from 2007 or later in order to assess any question about CTE as it was implemented after Perkins IV. I use the *High School Longitudinal Study* of 2009 which collected data about students who were ninth graders in the 2009-2010 school year. The same students were followed longitudinally with data collections in the spring of 2012, and fall of 2013 (immediately after high school graduation for most of the cohort). In addition to being collected at an appropriate time point, HSLS:09 captured appropriate data for research about CTE and college enrollment including high school transcripts and a rich set of variables about students' backgrounds. The background data were collected in the fall of 2009 (i.e., the base year), which was 9th grade for the respondents, and which is meaningful because it establishes student characteristics that predated their curricular selections.

Base year math scores were calculated for each student through a computer adaptive algebraic assessment. An additional follow-up survey of students was administered in 2016, and a final follow-up is planned for 2025. The future follow-ups are ideal for addressing questions of educational attainment, including future inquiries into topics of post-secondary persistence, choice of major, and earnings.

The analytic sample for this study includes all first-time 9th graders in public schools where CTE was offered, who graduated by the end of the 2012-13 school year, and for whom a high school transcript and college matriculation outcome was available. Additionally, in order to ensure that all students had equal opportunity to pursue their CTE program without interruption, only students who did not transfer schools were included in the sample. Students were included in the nationally representative analyses if they had a non-zero analytic weight. (N = 9,400).

Private school students were excluded from the sample because private schools do not receive Perkins funding and are not under equal pressure to comply with its design changes.

Missing data. Missing data were treated via multiple imputation using chained equations, which reduces bias more than listwise deletion or alternative forms of imputation (Allison, 2002). I conducted the imputation with all analytic variables as well as sampling frame variables and analytic weights to preserve the relationships in the data between variables (Enders, 2010; Reiter, Raghunathan, & Kinney, 2006). Observations in which the dependent variables were missing were included during the creation of the imputed models, so as to further preserve the relationships in the data between all variables. They were then deleted listwise from the data so that no student had an imputed dependent variable in the analysis (Von Hippel, 2007).

Measures

The dependent variable of student enrollment in college was measured through a survey that was mailed several months after graduation, in the fall. Students who indicated they were attending college were asked what degree or credential they were seeking. The options were: a bachelor's degree (usually a four-year degree), an associate's degree (usually a two-year degree), a certificate or program from a school that provides occupational training (e.g., cosmetology), or classes towards no specific program. I used these responses to create two different dependent variables. The first was whether the student enrolled in any college course (i.e., taking courses at any of the above listed levels). The second dependent variable was, among students that are seeking a credential, whether they enrolled in a two-year (associate's degree or certificate/program) or a four-year (bachelor's degree) program.

I measured exposure to CTE as the number of non-duplicative courses completed in a program of study. To create this measure, I specified courses taken in a program of study as courses taken within one of the 79 programs of study from Advance CTE (Advance CTE, n.d.)—an organization of state CTE leaders. In order to match the courses from the Advance CTE programs of study to the HSLS:09 transcripts I coded each of the Advance CTE courses with a course code from the School Course for the Exchange of Data (SCED) catalog. Courses in the transcript are provided from NCES with SCED codes for all transcripts already attached. Using this crosswalk, I match courses to each of the 79 possible programs of study.

By using 79 programs of study as a guide I do not capture the true programs of study in place at students' schools. I do, however, capture course taking combinations that can be interpreted as meaningful CTE experiences, which is what programs of study are designed to provide. For additional details about the construction of student progress in a program of study, see Chapter II.

To address the quantity and quality of students' academic experiences, I use Austin's (2020) measure of curricular intensity. To compute this, I use values for a student's total number of English credits taken, total number of laboratory science credits taken, the highest math course taken, and whether a student ever took an advanced placement (AP) course. The highest math course values range from zero (no math) to six (calculus); participation in an AP course is given a value of zero (did not ever take) or one (took at least one AP course). These four values were multiplied by standardized factor loadings that indicate their relationship with the latent construct of curricular intensity. These factor loadings are dataset specific, but loadings for HSLS:09 are available publicly (Austin, 2020). The loadings from the confirmatory factor analysis effectively act as weights for the contribution of each of the four factors within this cohort to the overall measure of curricular intensity. I then summed the weighted values of each of the four variables to create one single value of curricular intensity for each student. Additional details on the computation of curricular intensity are available in Chapter II.

Table 4.1

Mean Values and Proportions of Sample

	All High School Graduates	College Enrollees
Background		
Age at Sep 1, 2009	14.61	14.56
Female	0.52	0.53
Socioeconomic Status	-0.01	0.15
Math Score	0.11	0.28
Expect to Attend College	0.86	0.92
Race		
White	0.56	0.59
Black	0.11	0.10
Hispanic	0.21	0.18
Asian	0.04	0.05
Other	0.08	0.08
Transcript Variables		
GPA	2.87	3.06
Curricular Intensity	5.37	5.85
Total Progress in a CTE Program	1.75	1.74
N	9,400	6,420

Note. Standard Deviations not included because means are average point estimates from imputed datasets. Socioeconomic status and math score were constructed as standardized variables with a standard deviation of 1. Before imputation, the standard deviation of GPA, curricular intensity, and CTE progress were, respectively, 0.70, 2.05, and 1.10. Analytic weights used. Sample sizes rounded to the nearest 10, in line with NCES guidelines for restricted-use data.

Other independent variables used to adjust for differences between students at the beginning of high school, before exposure to CTE, are included as measured at the start of high school. These variables include student characteristics of age, sex, race, socioeconomic status (SES), math score in the fall of 9^{th} grade, and educational attainment expectations. Transcript-derived variables include the aforementioned student progress in CTE, curricular intensity, and student GPA. Table 4.1 provides descriptive statistics of the sample.

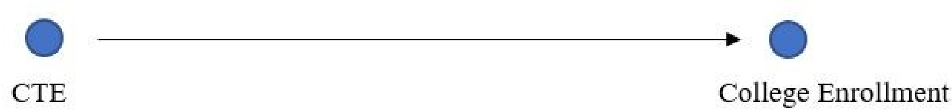
Several of the included adjustment variables are correlated with curricular intensity, such as GPA, and prior math score. By including correlated constructs, the interpretation of curricular intensity will change. Instead of representing all of a student's quantity and quality of academic coursework, it will instead represent the portion that is not associated with GPA or prior math scores. As detailed in Chapter II, I judge the interpretation of curricular intensity under such circumstances to represent the portion of a student's academic course quantity and quality that is due to student engagement and structural opportunity.

Analytic Approach

If it were possible to randomize the assignment of students to participate in CTE, then assessing the relationship between CTE and the level of college enrollment would be straightforward. A causal graph could be used to depict the relationship under the randomized conditions. It would show a direct arrow from CTE to college enrollment (Morgan & Winship, 2015). Such a causal graph is shown in Figure 4.1.

Figure 4.1

Naïve Causal Diagram of Career and Technical Education and College Enrollment



Randomization in this case is not ethically possible. However, I still estimate this model as the naïve estimation of the relationship between CTE participation and college enrollment in order to establish the baseline relationship and inform later models. By establishing the naïve model, I set an anchor for what happens in general trends without including any adjustment variables, and provide context for discussing results. This logistic regression model is specified as follows:

$$\log\left(\frac{p(CollegeEnrolled)}{1 - p(CollegeEnrolled)}\right) = \beta_0 + \beta_1 CTE \qquad (1)$$

where p is the probability of enrolling in college and *CTE* is a count of the number of courses taken within a program of study. All standard errors are clustered at the school level and weights are used for nationally representative estimates. The interpretation of β_1 is the naïve representation of the relationship between participation in CTE and enrolling in college. I expect there to be no difference between CTE and non-CTE students in overall college enrollment. However, due to the alignment of CTE with two-year programs I expect that CTE participation will be associated with greater probability of enrolling in two-year programs relative to their non-CTE peers. The naïve estimate shows what the overall trend is for CTE students without accounting for any other factors.

I then move to a model that adjusts for background characteristics in order to see how the association between CTE participation and college going changes in a more informed model:

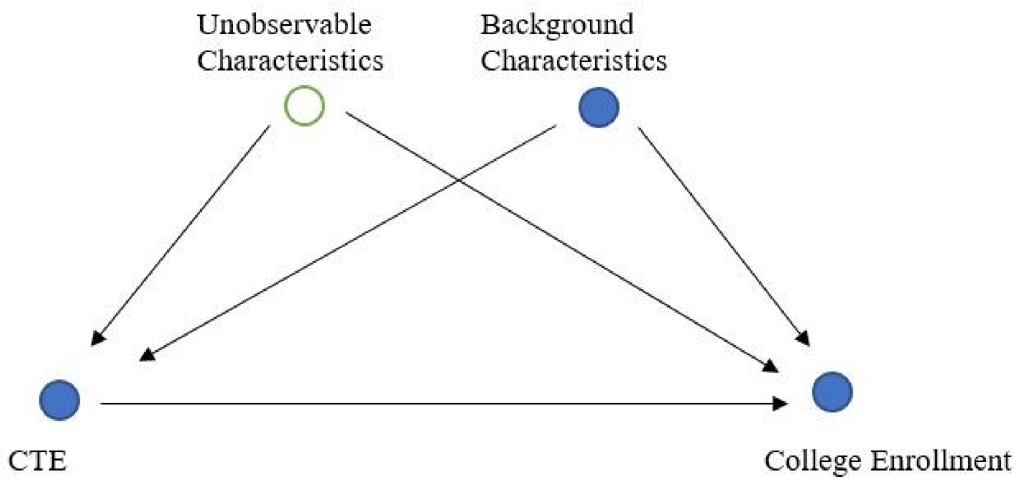
$$\log\left(\frac{p(CollegeEnrolled)}{1 - p(CollegeEnrolled)}\right) = \beta_0 + \beta_1 CTE + \beta_2 \boldsymbol{X} \qquad (2)$$

where p is the probability of enrolling in college, *CTE* is a count of the number of courses taken within a program of study, and $\boldsymbol{X}$ is a vector of student characteristics measured in the fall of 9th grade. The inclusion of these characteristics adjusts for differences among students that predated their CTE selections, or may have driven their CTE selections. The vector $\boldsymbol{X}$ also includes student GPA, which is influential in a student's likelihood of persisting to post-secondary education. All standard errors are clustered at the school level and weights are used for nationally representative estimates.

In this model, β_1 represents the association between CTE and college enrollment after adjusting for observable background characteristics. I suspect that in this more sophisticated model that the observed association between CTE and the outcome will diminish as the positive student traits are accounted for. This is the model used in early observational work into college and CTE (Arum & Shavit, 1995; DeLuca, Plank, Estacion, 2006), but does not account for unobserved characteristics as shown in Figure 4.2, where the hollow bubble indicates an unobservable variable. The inability to account for unobserved characteristics that are correlated with both participation in CTE and enrollment in college biases the estimations of the relationship.

Figure 4.2

Causal Diagram between Career and Technical Education and College Enrollment with Background Accounted For



I, then, proceed to include the adjustment for curricular intensity into the model. The intuition for how academic course scheduling, and scheduling in general fits into the map is shown in Figure 4.3. Both background and unobservable characteristics affect CTE through the scheduling of academic courses. If a student is unable to schedule CTE courses, the background and unobservable characteristics continue to affect the outcome variable (as well as other variables they influence), but they cannot influence the relationship between CTE and college enrollment.

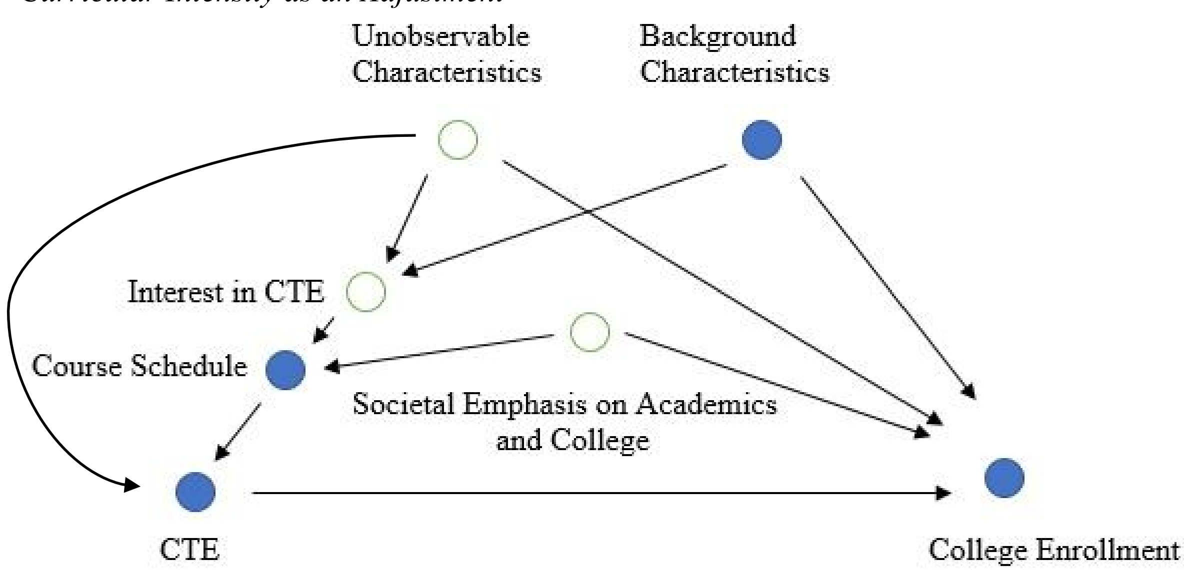
Figure 4.3 includes the unobservable societal emphasis that influences both student's academic coursework and their interest in college and degree type. This influence is likely to be almost entirely observed through the quantity and quality of academic courses in students' schedules. Therefore, I extend my model to include an adjustment for curricular intensity, which blocks the path from societal emphasis on academics and college to CTE and removes bias. The statistical model changes from previous models as follows:

$$\log\left(\frac{p(CollegeEnrolled)}{1-p(CollegeEnrolled)}\right) = \beta_0 + \beta_1 CTE + \beta_2 CurricularIntensity + \beta_3 \boldsymbol{X} \qquad (3)$$

where p is the probability of enrolling in college, *CTE* is a count of the number of courses taken within a program of study, curricular intensity is a measure of academic experience, and $\boldsymbol{X}$ is a vector of student characteristics measured in the fall of 9th grade in order to represent students at the outset of high school when they begin to choose their CTE program of study, and begin to build their GPA throughout high school. All standard errors are clustered at the school level and weights are used for nationally representative estimates.

Figure 4.3

Causal Diagram between Career and Technical Education and College Enrollment with Curricular Intensity as an Adjustment



Model 4.3 allows for the interpretation of CTE on college enrollment without the bias of the contemporary emphasis on college and academics. It falls short of providing a causal

inference, however, because it does not intercept all unobserved information about students that affects both participation in CTE and college enrollment decisions. There is likely still an arrow between CTE and unobservable characteristics that is driven by variables such as neighborhood characteristics. These unobservable characteristics can determine whether CTE is even offered within a local school, which programs are offered, and whether the student has approval from his parents to pursue personal interests in courses.

The same coefficient as previously, β_1, will be used to interpret the effect of CTE on college enrollment. If the coefficient is significantly positive, it indicates that participation in CTE is associated with increased odds of enrolling in college, and vice versa.

Next, I estimate the association between CTE and the decision among eventual college students to select into a four-year degree or a two-year degree. The model remains the same, except for the change in dependent variable and conditional sample. The following model shows how the slight changes affect model three. Changes to models one and two are not shown, but follow the same pattern of change in dependent variable and conditional sample.

$$\log\left(\frac{p(4yrDegree)}{1-p(4yrDegree)}\right) \mid (CollegeEnrolled = 1)$$

$$= \beta_0 + \beta_1 CTE + \beta_2 CurricularIntensity + \beta_3 \boldsymbol{X} \qquad (4)$$

where the probability of attending a four-year degree is compared to the probability of attending a two-year degree, conditional on having enrolled in college. When evaluating the β_1 coefficient from the models predicting two- or four-year college (i.e., college level), a negative coefficient would indicate a higher probability of enrolling in a two-year program. If CTE participants are more likely to enroll in a two-year program, it may be due to CTE's articulation with two-year programs. A positive β_1 coefficient would indicate that CTE participants are more likely to attend four-year programs, which could be due to an increased level of engagement or confidence derived through CTE participation.

Results

Table 4.1 reports descriptive information about the two samples. Not surprisingly, students who enrolled in college had higher levels of GPA, curricular intensity, and algebraic math scores. Somewhat surprisingly, there was no discernable difference in CTE progress between the two groups. This lack of difference is likely at the root of why the models estimating the association between CTE and college enrollment all indicate a non-significant relationship between them in Table 4.2.

The results in Table 4.2 collectively indicate that CTE has no relationship with college enrollment. The steady, non-significant estimates of the association between CTE participation and college enrollment suggests an absence of any relationship. The remarkable lack of change in the coefficient of CTE as adjustment variables are included in the analyses may indicate a complete absence of a relationship between CTE and college enrollment.

The third model in Table 4.2 indicates that curricular intensity is highly correlated with attending college. Its inclusion in model three reduces the magnitude of the association of several predictors and college enrollment. The magnitude of the estimated association college enrollment and the predictors of race, expecting to attend college, and GPA all decrease by meaningful amounts.

Table 4.3 reports results from the models that estimate the likelihood of enrolling in a four-year degree instead of a two-year degree, upon deciding to enroll in college. The naïve model indicates that students who participate in CTE are more likely to enroll in a two-year program instead of a four-year. This association is robust to the inclusion of background and high school performance characteristics, but becomes insignificant when curricular intensity is included in model three. This indicates that there is no evidence that participation in CTE influences a student's decision between two-year or four-year programs. It does provide some evidence that the decision about two-year or four-year programs is associated with the student's level of academic preparation, which is represented by curricular intensity.

Table 4.2

Log Odds of Enrolling in College at any Degree Level

	1	2	3
Background			
Age		-0.29**	-0.26**
		(0.09)	(0.09)
Female		0.15	0.15
		(0.09)	(0.09)
Socioeconomic Status		0.56***	0.51***
		(0.08)	(0.08)
Math Score		0.05	-0.07
		(0.06)	(0.06)
Expectation of Attending College		0.59***	0.19***
		(0.14)	(0.14)
Race (Reference: White)			
Black		0.78***	0.63***
		(0.17)	(0.17)
Asian		0.80***	0.58*
		(0.23)	(0.23)
Hispanic		0.70***	0.58***
		(0.15)	(0.15)
Other		0.51**	0.46*
		(0.18)	(0.18)
Transcript Descriptives			
GPA		1.19***	0.96***
		(0.07)	(0.08)
CTE Progress	-0.01	-0.04	-0.04
	(0.04)	(0.04)	(0.04)
Curricular Intensity			0.21***
			(0.03)
Constant	1.55***	1.05***	0.12
	(0.09)	(0.15)	(0.22)
N	9,400	9,400	9,400

Note. GPA centered around mean GPA. Weights used for nationally representative estimates.

Table 4.3

Log Odds of Enrolling in Two-Year vs Four-Year Programs, Among College Enrollees

	1	2	3
Background			
Age		-0.13	-0.07
		(0.10)	(0.10)
Female		-0.17	-0.18
		(0.10)	(0.10)
Socioeconomic Status		0.56***	0.48***
		(0.07)	(0.07)
Math Score		0.39***	0.13
		(0.07)	(0.08)
Expectation of Attending 4 Yr. College		0.96***	0.77***
		(0.19)	(0.18)
Race (Reference: White)			
Black		0.64**	0.47*
		(0.19)	(0.19)
Asian		0.56**	0.15
		(0.19)	(0.19)
Hispanic		0.11	-0.12
		(0.15)	(0.14)
Other		0.02	-0.08
		(0.14)	(0.14)
Transcript Descriptives			
GPA		1.16***	0.79***
		(0.09)	(0.09)
CTE Progress	-0.12**	-0.11**	-0.08
	(0.04)	(0.04)	(0.04)
Curricular Intensity			0.41***
			(0.04)
Constant	0.87***	-0.25	-2.24
	(0.08)	(0.20)	(0.20)
N	6,420	6,420	6,420

Note. GPA centered around mean GPA. Weights used for nationally representative estimates.

Discussion

I find that CTE has a null relationship with college enrollment. In other words, participation in high school CTE is not associated with a student's decision of whether to enroll in college. Students participating in CTE after the redesign effected through Perkins IV are just as likely to attend college as students who never enroll in CTE. This result differs from and identifies weaknesses in the models used in earlier work that showed dramatic decreases in college enrollment for CTE students (DeLuca, Plank, & Estacion, 2006), but is in line with work that used more recent data, from the early 2000s data (Gottfried & Plasman, 2018). The results of this study can be considered a win for educational stakeholders who worked to update CTE away from a design that tracked students into the labor force and away from college.

Once students decide to go to college, there is no meaningful relationship between participating in CTE and choosing a two-year versus a four-year program. This may be a consequence and limitation of estimating the association of CTE participation as a single experience, common to all participants. In actuality, students participate within a specific area of CTE, known as career clusters. Although CTE is designed to articulate with two-year college programs, some career clusters, such as STEM, may be more naturally amenable to four-year programs. This presents the potential for students who are swayed after participating in CTE towards a two-year degree programs to be "balanced out" by those who were swayed to a four-year degree.

The best predictor of a student's post-secondary enrollment is GPA. However, curricular intensity is also a meaningful and significant predictor of college enrollment that should be considered in future research on college enrollment generally, as well as in studies of CTE and college.

Future research is needed to determine if the same results are found for students in every career cluster, or if students in career clusters that have lower average levels of curricular intensity attend college less frequently. The data I used for this study do not allow for the pursuit of this follow-up question because, although large overall, they do not have a large enough sample of students in all CTE clusters to allow for estimates by career cluster.

The findings presented here of a non-significant relationship between CTE and college-going, and choice of two- or four-year program bode well for CTE. CTE is currently riding a wave of support at local and federal levels because of its perceived role in increasing levels of college and career readiness. These findings cannot prove the definitive absence of any relationship between CTE participation and college enrollment decisions, but they do provide some evidence that students may indeed prepare for careers without reducing college readiness.

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Chapter V

Conclusion

This dissertation began by calling attention to the historic practice of tracking in CTE's predecessor, vocational education. Students' participation in vocational education was largely based on their academic performance (Rosenbaum, 1976). Participation in the vocational track was common among students from low-SES families, and, often, they continued to college at lower rates than their peers (Gamoran & Mare, 1989). Changes in legislation and in school organization eliminated formal tracks, and encouraged all students to participate in CTE. These changes suggest that a student's academic schedule may no longer be associated with enrollment in CTE.

In this dissertation, I attempt to evaluate this claim. To do so I compare the academic course load of CTE students compared to non-CTE students, as well as the academic course load of CTE students who are enrolled in 16 different career clusters.

In order to investigate the association of CTE with academic course taking, I identified a recent refinement (Austin, 2020) of an established measure of academic course taking (Adelman, 1999; 2006), known as curricular intensity. Curricular intensity is the quantity and quality of students' academic coursework. This simple definition represents what curricular intensity is, but its interpretation changes as related covariates are included in the statistical model. Other variables such as GPA, prior math scores, race, and SES are known to influence students' academic course taking, or curricular intensity. This leaves unmeasured factors, such as engagement or structural opportunity differences, as factors that explain the core differences in curricular intensity, as discussed in Chapter II.

I use *curricular intensity* to address salient questions about CTE in three papers. I measure CTE participation as enrolling in a series of connected, non-duplicative, cohesive CTE courses (i.e., a program of study). Participating in CTE via programs of study is the method of participation introduced and prescribed by a federal funding bill for CTE, known as Perkins IV (Threeton, 2007). This dissertation contributes new knowledge by more accurately measuring student participation in CTE via programs of study and the results of participation in a nationally representative sample according to the design that began to govern schools' CTE offerings and student participation therein after 2006.

In the following I briefly review important findings from each chapter, explain how the results extend the body of literature, and propose next steps for further research in each area. I then elaborate on how the findings of the three chapters work together to improve the knowledge base on CTE.

Chapter II examines the connection between academic course taking and CTE participation. I compare the curricular intensity of CTE students to non-CTE students, and I compare the curricular intensity of CTE students across the 16 different career clusters. I find that the level of curricular intensity does not differ between CTE and non-CTE students. The same is not true within CTE. Curricular intensity differs significantly within CTE, by career cluster. There is a distribution of curricular intensity values among students. Students with low levels of curricular intensity tend to enroll in specific clusters of CTE, (e.g., transportation or manufacturing). By contrast, students with high levels of curricular intensity tend to enroll in different career clusters (e.g., STEM). When looking at CTE overall, no evidence of sorting by curricular intensity appears because both low- and high-curricular intensity students participate. However, full analyses of the data show that students participate in distinctly different career clusters of CTE.

The differences of curricular intensity between career clusters are explained in part by factors such as SES, race, GPA, and prior math scores. These differences remain significant even after adjusting for those factors. The remaining variation in curricular intensity is likely indicative of structural inequality. The structural inequality is built in CTE's current situation because schools cannot offer meaningful programs of study in all 16 recognized career clusters, so they must pick which to offer. Schools that serve students from neighborhoods with means may be more likely to offer CTE career clusters that differ from those in schools serving students in economically stressed communities. The distribution of curricular intensity scores reported in Chapter II may be a function of the courses that were offered in students' schools. Suggested directions for future research include verifying structural inequality, as well as reasons for its continuance. Additionally, future research is that investigates the differences in student outcomes between the 16 career clusters would be helpful. This may seldom be possible because of the enormous sample sizes such research designs would require. However, where possible the inclusion of all 16 represents an optimal CTE specification. This analytic burden could be eased by future research into a typology that compresses the 16 career clusters into fewer groups that appropriately model CTE student heterogeneity, thus allowing the retention of larger sample sizes.

Chapter III reports results of CTE's association with the probability of a student dropping out of high schools. I find that CTE is consistently associated with decreased odds of dropping out across multiple specifications. Those odds of dropping out decrease further for every class a student takes in a program of study. The benefit of reduced dropout probability is observed for all students, including those in advanced mathematical coursework, although their odds of dropping out are low, regardless of CTE participation. Enrollment in advanced math courses is indicative of a high curricular intensity level, which is more predictive of drop out than SES. The decreased odds of dropping out provide evidence that CTE's association with decreased dropout may function through increased student engagement. Future research is needed to clarify whether the associated decrease in dropout for CTE students occurs for students who did not select into CTE, but who were enrolled in CTE courses because of school policies.

Chapter IV reports results of CTE on students' enrollment in college. I also explore whether college enrollees choose a two-year or four-year program after participating in CTE. The change in design of CTE in 2006, under Perkins IV, required that programs of study must be aligned with a two-year post-secondary program (Dortch, 2012). This was a noteworthy change because the new goal of enabling CTE students to enroll in college contrasted with historic trends of lower rates of college going among CTE students (Arum & Shavit, 1995; DeLuca, Plank, & Estacion, 2006). I find that participation in CTE has no association with a student's probability of enrolling in college. Further, participating in CTE has no association with a student's decision to enroll in a two-year or four-year program, after adjusting for curricular intensity. These results are exciting because they allow high school counselors and teachers to recommend CTE to any interested student, without fear of adverse effects on later educational attainment.

Future research is needed to build on this study to look deeply into the experience of CTE participants when they are at two-year and four-year degree programs in college. Several studies have documented the higher earnings that are associated with CTE participation in high school, but none have investigated whether CTE participants graduate from college, earn higher wages, and/or have less student debt. Future research also should investigate the relationship between each of the career clusters and college. For example, some career clusters that do not align well with four-year degrees may lead to increased student enrollment in two-year degrees.

Taken together, I find that CTE participation is beneficial to students, though structural inequities may still prevail. In short, this study in three parts indicates that CTE may still be used as a sorting mechanism, may help students who are disengaged in academic coursework to persist towards graduation, does not harm students' likelihood of enrolling in post-secondary education.

The findings raise an interesting overarching question. If some sorting of students has persisted across career clusters (Chapter II), but the historically negative outcomes of sorting have been replaced by positive outcomes of higher engagement, less dropout, and more college enrollment, should tracking be reinstituted in American public education?

My findings do not support an argument in favor of tracking. I observe benefits from CTE participation, but they occur in an environment without tracking in which students of varying academic backgrounds can—and do—enroll in the many of the same CTE courses. My findings cannot speak to what would occur if students were strictly tracked again by pre-ordained paths to education and occupations. We see in nationally representative data that evidence of some sorting within CTE by curricular intensity is not harsh. There are some high curricular intensity students in automotive classes and some low curricular intensity students in STEM classes. This heterogeneity is an important component in achieving the intended and observed benefits of CTE's current model.

Rather than thinking about the results of this study to support a return to tracking, I believe they show two things about sorting. First, occupational interests of students are not bounded entirely by their academic curriculum. Second, that structural opportunities may not yet be fully equitable.

Finally, across chapters, curricular intensity emerges as an important variable to include in analyses of the processes and effects of CTE. Students' academic coursework highly influences the type of CTE that the student participates in.

The increased interest in CTE by students and stakeholders, alike, warrants additional research on the relationship between CTE and academics in high school and beyond. The inequality that Lucas (2008) predicted would be produced by the new design of CTE has not taken hold entirely. Additional research that builds on the contributions of this study will continue to investigate questions of equity and CTE. This is a core question regarding CTE because it has been entrenched in schools nationally for 100 years. This provides CTE enormous potential because it is built into American education, meaning that nothing about it needs to scale up—it already is scaled up. It is as a familiar intervention for students that they are frequently excited to participate in. However, its legacy in American schools also gives reason for the continued importance of research into equity within CTE. Its potential to help swings both ways and can also harm if left unchecked, as with tracking practices in vocational education. Yet its ubiquitous presence in schools underscores the enormous potential it holds as a key in preparing students for the labor market and post-secondary education.

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